THE USE OF BRAND PREFERENCE MEASURES FOR MARKET SEGMENTATION

By

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The concept of market segmentation has a firm theoretical base in microeconomic theory dealing with imperfect competition and has become one of the most pervasively discussed topics in the marketing literature of the past twenty years. Early research in segmentation focused upon internalized characteristics of the consumer and tended to ignore situation specific aspects of the purchase sequence. As a result of this deficiency much of this research was rather unproductive in developing predictive ability.

In response to this predictive weakness, an orientation has developed more recently which focuses on the interface between the consumer and the product class. Known as the product stream, it considers values, needs, and attitudes relevant to the product

under analysis to be the preferred segmentation bases. Unfortunately, proponents of this approach have not presented any formalized methodology, and other researchers have limited their inquiry to the use of measures obtained from various formulations of expectancy value models.

Such procedures are fraught with problems relating to product attribute specification and data collection. This study proposes that brand preference measures provide an alternative segmentation base which is an unobtrusive way of obtaining similar information as well as being more closely related to overt behavior and serving as an input for multidimensional scaling procedures. A geometric space representative of the consumer's perception of the product class which can serve as a guideline for strategy development can be derived from multidimensional scaling algorithms.

A survey of housewives from three cities in Florida was conducted covering two product categories for the purpose of comparing preference measures with attribute importance measures for isolating market segments. The comparison was undertaken to determine which measure lead to segments which fulfilled stated criteria for meaningful market segmentation. Specifically, the issues of concern dealt with segment identification, brand purchasing, and responsiveness to marketing mix elements.

Results indicated that both measures are equally useful for identifying segment membership. However, the preference measures lead to segments which are much more highly associated with brand choice, although only marginally more sensitive to marketing mix elements. These results were more stable and significant for the analgesic market than for the hard-surface floor cleaner market.

The geometric product spaces that were derived from the preference measures were found to be less useful for strategy development than had been thought. Still, their validity seems well founded due to their relationship with brand usage data. While some study objectives were not achieved, taking the results as a whole indicates that brand preference measures are useful for understanding the constructs underlying market segmentation.

CHAPTER I
INTRODUCTION

The propositions underlying the concept of market segmentation are that consumers are different, that these differences are related to differences in market demand, and that segments of consumers can be isolated within the overall market (Engel, Fiorillo, and Cayley, 1972, p.2). The management strategy of targeting the firm's efforts toward particular segments results from this market segmentation concept. Thus, it is apparent that market targeting is a two stage process. First, it requires the identification of a number of consumer groups which are distinct from each other in a meaningful way. Second, elements of the firm's marketing mix need to be modified in order to provide a marketing program specifically tailored to one or more of the groups so as to provide for maximum profitability.

The early published research in market segmentation focused upon internalized characteristics of the consumer and tended to ignore situation specific aspects of the purchase process. As a result, much of this research proved to be rather unproductive in developing predictive ability. A more recent orientation has developed in marketing

research which focuses on the interface between the consumer and the product class. The primary concern of this orientation is the identification of consumers of particular brands rather than products (Boyd, Westfall, and Stasch, 1977).

Wilkie (1970) has named this person/product orientation the "product stream" and it consists of two main avenues of investigation. First, the focus is on the importance various product attributes have for brand choice decisions. Labeled benefit segmentation by Haley (1968), it considers needs and values relevant to the specific product class as the preferred segmentation bases. Second, the focus can be on the perceptions consumers have of the various brands within the product class.

The product stream approach is managerial in nature in that it is primarily concerned with brand level choice behavior. The idea behind the orientation is to identify target segments of consumers who either desire similar product attribute configurations or who perceive similar brand attribute relationships. Research findings can then be used to create new brands or to position existing brands so they will differentially appeal to specific segments. Thus, under this orientation segmentation is associated with both the person and the product and not merely inherent characteristics of the consumer.

Although the applicability of brand perceptions as a segmentation base is accepted by many theoreticians (Boyd, Westfall, and Stasch, 1977), published reports using the

product stream orientation have all focused on product benefits desired by consumers. These reports have primarily consisted of post hoc explanations of market success which have made very favorable claims for benefit segmentation's usefulness as a segmentation tool.

Unfortunately, the proponents of benefit segmentation have not presented any formalized procedures, and while benefit segmentation methodologies of a proprietary nature that work well in practice undoubtably exist, there has not been any general agreement among researchers in the field on the value of alternative procedures. Thus, development of a product segmentation methodology as an alternative to benefit segmentation that would provide a framework for the practitioner as well as conceptual vigor would be beneficial to the marketing discipline. This is especially true considering the limitations of current knowledge dealing with consumer responses.

Purpose

The worth of a segmentation methodology can be aided by the use of a theoretical framework for relating the methodology to specific segmentation criteria. An individual behavioral framework as viewed from a segmentation perspective is presented in Figure 1. While not intended to be a model of consumer behavior, the figure should provide a simplified framework for relating alternative segmentation bases to overt behavior.

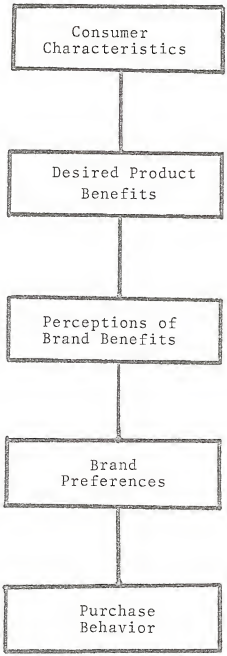

Figure I

A BEHAVIORAL FRAMEWORK AS
VIEWED FROM A SEGMENTATION PERSPECTIVE

The first box, consumer characteristics, was the focus of early segmentation research and used such descriptors as demography and personality. These descriptors make up the "empirical stream" (Wilkie, 1970) and are discussed in Chapter II. The next two boxes are the domain of the product stream. Desired product benefits have been used in a number of cases to isolate benefit segments who have similar needs with regard to the product class. As noted previously, perceptions of brand benefits have been proposed as a segmentation base but as yet no published reports have appeared using these measures.

Within the attitude literature a good deal of theory exists indicating that desired benefits and brand perceptions are combined according to some logical process to form brand preferences (Fishbein, 1967; Rosenberg, 1956; Cohen and Ahtola, 1971). Such preferences serve as direct antecedents of behavior. Therefore, the use of brand preference measures as the segmentation base has the advantage over benefits desired and perceptions of embracing information contained in both of these measures as well as being more closely related to overt behavior. Another advantage of employing brand preference is that they can serve as input for certain preference models, to be discussed below, which provide a pictoral representation of the consumers' cognitive structure regarding the product class.

Accordingly, this study proposes that brand preference measures should be added to the product stream orientation

since there is theoretical justification for linking the measures to specific behavioral criteria. The purpose of the study, then, is to compare preference measures against those used by researchers to create benefit segments as to their efficacy for isolating market segments. It must be kept clearly in mind that the goal is not to create unique or interesting segments, but rather to create segments that are meaningful in the sense that they provide for specific targeting strategy. This can be accomplished by careful delineation of market segmentation criteria that meet this goal.

Criteria

A number of researchers have advanced criteria for fulfilling the goals of market segmentation. Kotler (1976, p. 143) lists "measurability, accessibility, and substantiality." The triumvirate of "identifiability, variation in demand, and variation in response to marketing variables" has been proposed by Frank (1968, p. 136). Wilkie (1970, p. 13) has suggested "homogeneity within and hetergeneity between groups, usefulness as a correlate of behavior, and efficiency as a target for marketing tools."

In general these criteria have been proposed by researchers who are primarily interested in behavioral consequences and thus have focused on such issues as measurement and behavioral correlation. Using these and

attempting to approach the concept as related specifically to the product stream, the following three criteria are proposed as encompassing the requirements needed for successful segmentation:

1. Identification of homogeneous consumer groups.
2. Brand usage.
3. Sensitivity to marketing mix elements.

It must be clearly understood that each criterion is a necessary but not sufficient condition for segmentation. That is, an attempt to maximize a subset of them at the expense of the remainder will not lead to optimal segmentation. Each must be considered in relation to the others.

The identification of homogeneous consumer groups is, of course, the very essence of segmentation. The development of differential marketing programs is dependent upon the ability to identify distinct consumer groups. Homogeneity refers to the fact that these groups share a common property that can be used to discriminate among them. In the case of benefit segmentation the common property used to discriminate the groups is directly related to their desire for similar product benefits, whether they are values or needs. For brand preference segmentation the common property deals with consumer's preference for brands within the product class. The degree to which group members share the property is a relative one which depends on the measure used, the situation, and the time frame.

From a managerial perspective, market targeting is primarily concerned with purchasing at the brand level. Thus, the second criterion follows directly since segments should exhibit differential brand usage. Brand usage has three major dimensions: the brand consumers purchase, their loyalty to the brand, and the amount they purchase.

Although researchers have tended to ignore this aspect, sensitivity to marketing mix elements is absolutely essential to the segmentation process. If segmentation is to contribute to a profitable managerial strategy, the crucial consideration must be whether consumers in different segments respond in different degrees to changes in the firm's price, promotion, media, copy, and distribution policies (Frank, Massey, and Wind, 1972, pp. 133-34). Regardless of how well defined a target segment might be, if the segment members do not exhibit differential responsiveness to the firm's marketing decision variables, it is impossible to design a specific marketing program tailored for them.

After segmentation has been accomplished, the development of targeting strategy is of primary importance. Consideration must then be given to the size and competitive nature of the market segments identified. It is these two factors which primarily determine the profitability that can be achieved by cultivation of a particular market segment. Profitability, of course, is the ultimate goal of any strategy employed by the firm.

As previously noted, a firm base is used in this study to relate segments to the above criteria. That is, the concern will be with developing a segmentation scheme for identifying homogeneous consumer groups, and for relating these groups to their brand usage and sensitivity to marketing mix elements. Thus, the use of preference measures will be tested against the benefit scheme for their efficacy in achieving the three criteria and analyzed in terms of the implications for strategy they provide.

Organization

Since benefit segmentation and brand preference segmentation are subsets of market segmentation, they can best be understood as they relate to the entire segmentation field. Therefore, Chapter II (Historical Perspective on Segmentation) outlines the entire field with emphasis given to the various bases used to segment markets and discusses the major research findings associated with each.

Chapter III (Methodology) describes the preference models underlying this study and discusses the specific methods used to segment the consumers comprising the data base, the issues to be investigated, and procedures used to draw inferences.

An analysis of the results obtained and the conclusions drawn, as well as the meaning these have for

marketing management, is contained in Chapter IV (Results and Discussion).

Chapter V (Summary and Conclusions) presents an overview of the study findings and their implications, as well as some direction for future research.

CHAPTER II
HISTORICAL PERSPECTIVE ON SEGMENTATION

With the criteria for segmentation outlined in Chapter I firmly in mind, this chapter will now examine the history of segmentation research from the perspective of the various bases that have been advanced for its implementation. Wilkie (1970) has shown that these bases fall into two distinct approaches which he named the "empirical stream" and the "product stream." The former consists of the main stream of segmentation research and has focused on enduring personal descriptors of the target population attempting to relate segments defined in terms of these descriptors to product class purchasing behavior. The latter has consisted of both brand perception and benefit segmentation and has been a more recent innovation. Since this "stream" is more concerned with the interface between the consumer and the product, it has dealt with such variables as product and brand benefits, values, perceptions, and use occasions. For the reasons outlined in Chapter I it is proposed that brand perference measures be added to the "product stream" and a comparison of these two orientations is presented in Figure 2.

Throughout the history of consumer behavior a controversy has raged over whether variations in behavior

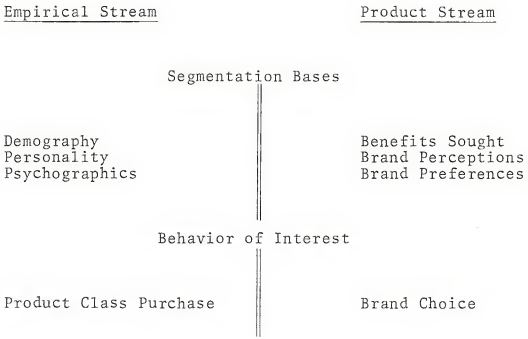

FIGURE 2

Comparison of the Major Approaches
to Market Segmentation

are due to stable traits residing within the individual or to the difference in the environmental situations. In point of fact, neither can be neglected, for even if situational variations were able to explain behavior completely, the question of how the individual transforms the situational input into behavioral output would still be unresolved.

Thus, an understanding of the goals of the product stream approach to segmentation and the state of knowledge which brought about its emergence requires a complete review of the segmentation literature. The various bases used for segmentation have been advanced in a roughly chronological order as each has attempted to improve upon earlier ones. While surveying the field it should be kept in mind that each base is not necessarily an alternative method but can be used in a complementary fashion.

Market segmentation received its primary impetus as a topic of research interest from a pioneering article by Wendell Smith (1956). Beginning from a firm theoretical base in microeconomic theory dealing with imperfect competition, he discussed the heterogeneity present among the components of both market demand and supply. He outlined two strategies available to the firm to deal with this situation. One of the strategies:

> . . . may consist of a program designed to bring about the convergence of individual market demands for a variety of products upon a single or limited offering to the market. This is often accomplished by

> the achievement of product differentiation through advertising and promotion. (Smith, 1956, p. 30)

Alternatively, under a strategy of market segmentation it is:

> . . . better to accept divergent demand as a market characteristic and to adjust product lines and marketing strategy accordingly. This implies ability to merchandise to a heterogeneous market by emphasizing the precision with which a firm's products can satisfy the requirements of one or more distinguishable market segments. (Smith, 1956, p. 30)

It was his position that the latter strategy is preferable since it evolves from variations on the demand side of the market and is a more precise adjustment of marketing effort to consumer needs. Due to this optimization of consumer satisfaction, segmentation provides for a stable market position with its attendant increased profitability.

On the other hand, Reynolds (1965, p. 111) argues that "market segments are more apparent than real." It is his contention that different products do not appeal to different segments but rather succeed because of the large number of switchers among the consumers comprising the "uniformity of the general American culture." Espousing the view that variety is the key element in describing consumer purchases he states:

> . . . One of the many characteristics people have in common is that they shift from one brand to another more or less frequently. Another is that they tend to be attracted to new brands and new products. (Reynolds, 1965, p. 107)

In a similar vein, Evans urged markets to build ambiguity into their products to avoid limiting their markets. Given a product with an ambiguous image, he believed that "there is a tendency for customers to read into it what they want. The things they value highly they attribute to their brand" (Evans, 1961, p. 366).

The above is an indication of the controversies surrounding the segmentation issue. Other controversies have arisen in that most of the early segmentation research was rather unproductive in developing predictive ability. In their zest to obtain correlations between purchase behavior and inherent characteristics they have, for the most part, ignored situation specific aspects of the purchase sequence. The assumption has been that internalized attributes of the individual are constant across time and environment, and that they will lead to consistent behavior responses regardless of any other external influences acting upon the decision. In defense of this position, De Bruicker (1973, p. 1) has pointed out that "measurement problems prevented the use of any but the most basic of personal descriptors in early segmentation analyses."

Geography

Historically, business enterprizes first segmented markets geographically (Haley, 1968). While geographical areas are the bases of differentiated marketing effort here, they are usually not due to any conscious effort to appeal to diverse consumer groups. Rather it results from either limited resources precluding national distribution or in response to specific product usages. Obviously then, while geography is an important concern for the firm it is of little consequence for the researcher.

Demography

Demographics have been the most widely used procedure for segmenting large markets into smaller groups. A profile of the consumer type in each group can be enunciated using primarily demographic variables. The usual focus is on such characteristics as income, age, social class, marital status, race, occupation, and the like. The usual procedure is to use these characteristics as discriminators of consumer choices regarding product usage and brand selection.

Such procedures have been widely used for media selection since it is assumed that there is a link between target groups so identified and responsiveness to communication messages. Such an approach has value and provides an

efficient use of demographic profile building. However, these variables have been shown to be incapable of differentiating consumer choices among a product class. Their only success seems to be in discriminating between various product class.

During the decade of the 1960's a number of studies were published searching for correlations between demographically defined segments and such behavioral variables as average purchase rate and brand loyalty. To mention some of the more noteworthy, Frank, Massey, and Boyd (1967) used the Chicago Tribune panel data for 1960 and 1961. The data consisted of purchase history for 491 households for each of 57 grocery product categories. The average proportion of the variance explained was .11 using 14 demographic variables as predictors. Rice cereals provided the highest proportion at .29, while the proportion was less than .20 for 46 of the 57 categories and less than .10 for 25 of the 57 categories.

The J. Walter Thompson panel data were reported on by Koponen (1960). He added personality measures to the demographic variables for two unidentified products and obtained .13 and .06 as the respected proportion of the variance explained. Using the same panel Hildegaard and Kruegar (1964) studied the toilet tissue purchasing behavior of 3206 households for the Advertising Research Foundation. They obtained a coefficient of determination of .12 for one-ply tissue and .06 for two ply tissue.

More recently, Gensch and Ranganathan (1974) used the Brand Rating Index data to study the purchasing behavior of 1550 consumers for six female grooming products and four grocery products. The product usage data were regressed against thirteen demographic variables and the proportion of the variance explained ranged from .02 to .26 with a mean of .09.

These studies were carried out within a regression framework and the results, in terms of R^2, were largely disappointing. In a survey of consumer behavior research, Ferber reported that cross-sectional analyses of household expenditures on food, clothing, shelter, and services indicate:

> . . . that these consumer purchases are influenced by a wide variety of socioeconomic characteristics; but, nevertheless, the proportion of variance in individual household purchases explained by these numerous factors is small, often on the order of .3 or less. (Ferber, 1962, p. 62)

The consistently low levels of R^2 achieved by using demographic variables as predictors lead to the conclusion that their usefulness as segmentation bases is severely limited at best. In reviewing the segmentation literature Frank concluded that:

> . . . for the most part socio-economic characteristics are not particularly effective bases for segmentation whether in terms of their association with household differences in average purchase rate or in

> response to promotion . . . In spite of the reliability that households exhibit with regard to brand loyalty, research efforts aimed at identifying the brand-loyal customer have been notably unsucessful. (Frank, 1968, p. 152)

In rebuttal Bass, Tigert, and Lonsdale (1968) have supported the feasibility of defining segments with demographic measures. While not disputing the evidence, they argue that it has been misinterpreted. It is their contention that the regression model is inconsistent with the purposes of segmentation and the low R^2's are indicative of high within group variance while differences in group means may still exist. They state:

> The absense of a satisfactory theory of individual behavior does not necessarily imply the absence of valid propositions about the groups' behavior. For marketing strategy, it is the behavior of groups, not persons, that is primarily important. (Bass, Tigert, and Lonsdale, 1968, p. 274)

Morrison (1973) agrees that R^2 is an inappropriate statistic to use in evaluating segmentation results. Through the use of probability models he indicated that:

> . . . it is perfectly consistent to have models which correctly identify variables that are useful for segmentation purposes and are still virtually useless in predicting individual purchases. (Morrison, 1973, p. 1218)

It would seem though, that inability to predict purchase rates because of high within group variances

when there are differences in group means results from considerable overlapping of the distributions of group purchase rates. Under such conditions segmentation could be improved by redefining the groups so as to minimize such overlap.

Twedt (1964) has answered critics of the regression approach by proposing that categorization of the dependent variable into a dichotomous one representing light and heavy users provides for more meaningful segmentation. He suggests that direct measurement of product usage is likely to be more efficient than regression analysis and profile matching. This contention is based on the fact that in most product classes 50% of the users account for in excess of 80% of the purchases. While such an approach has merit there are two major weaknesses in it. First, not all heavy users are available as targets for a particular brand since they may not differ in other respects. Second, focusing on the heavy users eliminates an effort to turn nonusers into users and light users into heavy users. It may well be that such an effort would result in profitable returns.

Thus, it is apparent that there is controversy over the usefulness of demographic variables serving as bases for segmentation. Regardless of the position espoused, the results have been far from impressive, most likely due to the fact that such an analysis investigates only direct links between specific characteristics and overt action.

There is no attempt made to understand the mediating responses and influences that are a part of the behavior. Without such an understanding, it seems only reasonable that predictive power is limited.

Personality

Partly in response to the limitations of demography researchers turned to personality to provide richer descriptions of consumer types. Personality is one of the more absorbing concepts used in applied marketing research. Virtually every component of consumer behavior has, at one time or another, been linked to personality. Unfortunately there has not been any general consenses among researchers on the meaning of the term personality.

After considering the communalities of a multitude of personality definitions, about all that can be said is that personality is the sum total of all the internalized attributes of the individual which result in consistent responses to the surrounding stimulus environment. Of primary importance in determining personality are constitutional, group membership, role, and situational influences (Lawrence and Seiler, 1965).

The typical approach here has been an attempt to find a relationship between batteries of personality tests and a myriad of product purchases. Such an approach has been variously referred to as "shot-in-the-dark" (Wells, 1975),

or "shotgun" (Kassarjian, 1971). The problem with the personality traits comprising the test batteries is that most of them are theoretically irrelevant to the product under consideration (Goldberg, 1976).

Perhaps the most widely debated study correlating product usage has been Evans' (1969) use of the Edwards Personal Preference Schedule to discriminate between Ford and Chevrolet owners. Evans' failure to find significant differences sparked a number of rejoinders and reanalyses during the early 1960's (Steiner, 1961; Winick, 1961; Evans, 1961; Kuehn, 1963; Evans and Roberts, 1963). While some other investigations of these data found some significant differences between Ford and Chevrolet owners, the results were far from impressive.

The Edwards Personal Preference Schedule has been used in a number of other studies including Koponen's (1960) analysis of the J. Walter Thompson panel data. He indicated that cigarette smoking was linked positively to sex dominance, aggression, and achievement needs but negatively to order and compliance needs. Claycamp (1965) used this instrument to discriminate between customers of banks versus savings and loan associations.

The Thurstone Temperament Schedule was used by Westfall (1962) to compare personalities of automobile owners and he was unable to find differences between brands as well as between compact and standard size owners. Noting the number of items left unanswered by subjects on

this instrument, Kamen (1964) concluded that opinion proneness is not related to food preferences.

The California Personality Inventory has been used to develop measures of innovativeness and opinion leadership in the areas of food, clothing, and appliances (Robertson and Myers, 1969, 1970; Bruce and Witt, 1970). Boone (1970) tried to relate these variables to the adoption of a community antenna television system.

The Gordon Personal Profile provides for measures of ascendancy, responsibility, emotional stability, and sociability. One or more of these variables were found to be weakly correlated with the use of analgesics, vitamins, mouthwash, chewing gum, and alcoholic beverages by Tucker and Painter (1961). Using canonical correlation Kernan (1968) found relationships between the personality variables and sets of decision behaviors even though individual correlations were insignificant.

Considering the weaknesses of personality measures as predictors of consumer behavior, it must be remembered that these instruments were originally developed to tap major personality traits underlying racial prejudice, marital incompatibility, proneness to commit suicide, and the like. The prediction of an individual's brand choice is a vastly different matter. Items used to measure psychological stability or imbalance are obviously not particularly germane to everyday marketing activities (Dhalla and Mahatoo, 1976).

In reviewing the use to which personality measures have been used, Kassarjian (1971) also notes that the reason for the low amount of variability explained may be due to the purpose for which these tests have been validated. Pointing out the need to rectify this situation he states:

> Clearly, if unequivocal results are to emerge, consumer behavior researchers must develop their own definitions and design their own instruments to measure the personality variables that go into the purchase decision rather than using tools designed as part of a medical model to measure schizophrenia or mental stability. (Kassarjian, 1971, p. 415)

On the other hand, Wells (1966) calls into question the fact that people have personality traits at all. It is his contention that situational influences are so important that most often the environment has greater impact on behavior than anything which can be conceived of as a personality trait. He suggests that the basic idea asserting that personality traits exist needs to be reexamined. In summary he states:

> . . . that the environment is so important in determining consumer behavior and the problems of measuring personality traits are so difficult to handle in consumer studies that personality tests may never have much value in consumer work if by value you mean correlations high enough to predict behavior accurately. (Wells, 1966, p. 189)

On the whole then, when used on their own as segmentation bases, personality traits have proven to be very disappointing. At best personality is more likely to be associated with behavior towards a set of products, representing a pattern of behavior, than to any one product in particular (Goldberg, 1976). However, they may still be a useful adjunct to demographic data in describing a priori defined consumer groups. Specific to media selection, the availability of personality profiles of existing audiences would seem to offer an opportunity for message segmentation.

Psychographics

The need for psychological measures which have been developed with consumption in mind as well as the integration of personality theories with the statistical sophistication of computer technology has led to an approach called psychographics, or lifestyle segmentation. It has its roots in the empirical reality that for some products, purchase is more dependent on the individual's stage in the life cycle than on personality.

The concept of lifestyle and its relationship to marketing was introduced by Lazer, who referred to it as:

> . . . a systems concept. It refers to a distinctive mode of living in its aggregate and broadest sense . . . It embodies the patterns that develop and emerge from the dynamics of living in a society. (Lazer, 1963, p. 141)

Since then, the methods for measuring lifestyle patterns and the determining of psychographic segments has been refined. The usual procedure is to divide the market into segments by means of paper and pencil inventories of activities, interests, opinions, values, attitudes and the like using techniques of numerical taxonomy and factor analysis. Unfortunately though, the segments uncovered by these methods, when correlated with actual purchase behavior, account for only 10% or less of the variance (Kassarjian, 1971).

It must be pointed out however, that these techniques, while extremely appealing, lack a conceptual framework and are marked by the absence of theoretical foundations. Thus, the possibility of obtaining a spurious structure is so high and results so inconsistent that it suggests statements made about psychographic segments are on very weak ground (Kinnear and Taylor, 1976). Yet they seem to show some value and thus, their integration into a consistent theoretical frame should be of immediate importance.

Closely related to this lack of a conceptual framework are the issues of validity and reliability. These are particularly salient due to the widespread use of "homemade" psychographic items and scales in a number of studies (Wells, 1975). Commenting on that issue he says:

> In view of the reservations already expressed as to the reliability and validity of segmentation procedures it might seem that the wisest course would be to ignore

> psychographics until the procedures have been thoroughly validated. But again, one must consider the alternatives. Marketers know the customers for a product or a service are frequently not much alike. They know that empirical segmentation procedures hold out the possibility of new insights into how consumers may be divided into groups. And they know that the reliability and validity of segmentation procedures have not been established beyond all doubt. Given that dilemma, many marketers have elected to conduct and to use segmentation studies even when fully aware of the art's imperfections. (Wells, 1975, p. 208)

The degree of specificity inherent in psychographic measures has also received a caveat from Wilkie and Cohen (1976). They point out that general psychographic measures meant to be applicable across product categories can not also discriminate among product characteristics. Thus, there can be hardly any basis for between brand analysis. This problem has stimulated Dhalla and Mahatoo (1976) to propose that psychographic measures are meaningful only when they are situation specific and not of a generalized nature. The danger here is that when carried to the extreme, the search for predictive validity can lead to measures which are redundant of the behavior under consideration. What is needed is to find a middle ground between the extremes of measuring a basic underlying orientation, unlikely to have predictive validity, and measuring a situation specific orientation unlikely to have construct

validity (Goldberg, 1976). Obviously, this is a formidable task for researchers to handle.

Benefit Segmentation

All of the above segmentation bases fall under the rubric of the "empirical stream" (Wilkie, 1970) in that they have been concerned with personal descriptors of the consumer. In recent years as the need for more situation specific measures has become apparent, an orientation has developed which focuses more on the interface between the consumer and the product. Wilkie (1970) has dubbed this approach the "product stream" since its orientation is more managerial in nature in that it is primarily concerned with brand differences within the product class. Thus, this orientation tends to ignore product class issues and concentrates instead on brand positioning and image.

Under this approach, demographic and personality descriptors are demoted to the role of ancillary measures. Indeed, Yankelovich (1964) feels that the old assumption that demography is the best way of partitioning markets needs to be discarded. Reynolds (1965) places more emphasis on the product than on the consumer and asserts that needs for variety and specific uses result in the same individual purchasing different brands at different times.

As previously noted, reports of research using consumer perceptions of brands have been virtually non existent. In

the main this stream has been concerned with the measurement of consumer's desire for various product benefits.

The bases used for benefit segmentation have been the values, needs, and attributes relevant to the product under analysis. The concept was first discussed in the marketing literature by Haley (1968), who introduced it as a panacea for the shortcomings of earlier segmentation variables. In regard to geography, demography, and purchase volume he states:

> However, each of these three systems of segmentation is handicapped by an underlying disadvantage inherent in its nature. All are based on an ex-post facto analysis of the kinds of people who make up various segments of a market. They rely on descriptive factors rather than causual factors. For this reason they are not efficient predictors of future buying behavior that is of central interest to marketers. (Haley, 1968, p. 198)

Unfortunately, proponents of this approach have not presented any formalized methodology or procedures. As a matter of fact, Haley (1968) has even stated that successful segmentation can result from some form of esoteric intuition. This has been the problem with this entire avenue of investigation. It consists primarily of interesting findings and post hoc presentations of marketing successes attributed to the process. While this state of affairs is understandable due to the proprietary nature of the studies undertaken, researchers interested

in validating the usefulness of benefit segmentation have been forced to devise their own methods for partitioning of the market and testing their efficacy (Wilkie, 1970; Mitchell, 1974). Thus, there is great difficulty in adequately determining the value of the approach vis-a-vis more traditional approaches.

Market structure analysis is a related technique developed by Volney Stefflre from a background in psycholinquistics and anthropology (Barnett, 1969). This technique deals with ratings of consumer preferences for descriptions of proposed new products. When such a description is preferred over current brands, it is proposed that a market potential exists which can be capitalized on by developing the product so consumers perceive it as matching its description. Barnett (1969) indicates that this approach has been successful in introducing new brands but does not specifically present quantitative results.

Reynolds (1965) disagrees with this notion believing that segments tend to be somewhat artifactual, especially those defined a posteriori in terms of the product purchased. Given merely that two products seem to be different, he contends that it is an error to conclude that the consumers who purchase them must also be different and comprise separate market segments. It may well be that they appeal to the same general market's need for variety (Reynolds, 1965).

The fact that consumers may not differ on variables other than their purchase behavior does not diminish the usefulness of the segmentation concept according to Haley (1971). The real payoff of segmenting markets, he asserts, has to do with copy efficiencies which can increase the impact of advertising by as much as three-fold. Explaining his position, he states:

> In short, benefit segmentation is a tool for improving your communications with the group or groups of consumers selected as the market target by selecting themes which improve your chance of capturing the attention of your prospects and of involving them in your advertising. (Haley, 1971, p. 3)

While benefit segmentation has been primarily undertaken in a proprietary setting, the concept has interested a number of academic researchers who have used similar formulations to form segments. In general, benefit segmentation studies have been carried out by measuring consumers' beliefs about the attributes of a product and then clustering them on the basis of the relative importance of each in contributing toward satisfaction of their needs and desires. Some studies have used determinant attribute scores (Anderson, Cox, and Fulcher, 1976), or attribute affect scores (Mitchell, 1974). The list of attributes employed may include redundancies which are either real or perceived as real by consumers. The typical procedure is to use a large set of attributes (Calantone, 1976).

The belief underlying benefit segmentation is that consumers who desire similar attribute, or benefit, bundles will purchase the same brand. That brand is the one that they perceive as most adequately fulfilling their needs due to the congruence of its attributes. The benefits sought by consumers are presumed to be stable over time in a manner similar to the way demographics and personality exhibit stability (Wilkie, 1970). Also, there is some evidence that differences in benefits sought by consumers exist across product classes (Haley, 1968).

While most benefit segmentation results have not been subject to critical evaluation, they have sparked a trend toward the use of product specific attitude measures employed in a more rigorously demanding framework. These have not yet provided the hoped for degree of success. De Bruicker (1973) was unable to discriminate between consumers' brand preferences using perceived product benefits, attitude, and activity measures as alternative bases for segmentation. Wilkie (1970) found that brand purchasing behavior was predicted much better by behavioral intention scores than by segmenting consumers on the basis of the importance they attach to product attributes.

These results may in part be due to the fact that relying on natural clusters runs the risk of achieving spurious segments, since most clustering algorithms are data reducing tools devoid of theoretical grounds for specifying what segments should comprise (Dhalla and

Mahatoo, 1976). However, it still seems obvious that market segmentation's focus upon attitude domain measures will provide keen insight into the mediating processes involved in purchase behavior.

Given that benefit segmentation studies have used consumers' importance ratings for various product attributes, there are two broad issues involved in determing the attributes to be measured. The first, initial specification, concerns the manner in which a proposed list of product attributes, encompassing perceptual as well as objective characteristics, is generated by the investigator. The usual procedure has been to use some type of unstructured pretest to generate attribute lists.

Given this attribute list, inclusion in the model deals with the way the researcher uses this data. The question is, are all of the generated attributes applicable to all respondents? The typical study has ignored the possibility of idiosyncratic attributes and used them all for every respondent, assuming that all consumers have the same perceptual structure.

By ignoring differences in the perceptions of individuals, these studies seem to imply that product attributes are product specific and large in number. Most all would agree, however, that only salient attributes should be included. In most papers an a priori assumption is made that this is the case.

This issue has been investigated by Wilkie and Weinreich (1973), who hypothesize that improvements can be achieved when individual differences are allowed in the number and type of attributes used. The main concern then was with the criteria used for attribute inclusion. These researchers focused on attribute determinism as proposed by Myers and Alpert (1968).

Determinant attributes are those which are directly involved in brand preference or actual purchase behavior. When important product characteristics are approximately equally represented in the set of brands under consideration, then such an attribute is not particularly salient to the choice of any one brand. Thus, determinism incorporates both the idea of importance and variation in the evaluation of brands on an attribute.

The results of Wilkie and Weinreich's (1973) investigation indicate that attitudes can be efficiently described in predictive terms with fewer attributes than are typically gathered in marketing research. They also conclude that incorporation of only those attributes salient to the individual leads to significantly better results than inclusion of all available ones, and that the practice of using all attributes for every respondent is likely to understate the predictive power of an attitude model.

Resolving the two problems alluded to above, attribute specification and inclusion, for each individual

would require the researcher to gather a larger quantity of as well as more accurate information from each subject. The difficulty is that as data gathering instruments increase in complexity the validity of the subjects' responses goes down.

One reason for this is that many individuals in general are not aware of their beliefs and attitudes and, thus, cannot accurately report them. From a marketing perspective, Greenberg and Green have commented:

> In the investigation of a product category, it is frequently misleading to depend upon consumers to "truthfully" tell us what are the most salient dimensions or which product attributes are the primary determinants in their purchase decisions. (Greenberg and Green, 1969, p. 52)

Also, for the purpose of responding to simple written questionnaires, it has been estimated that at least 10% of the adult population in this country is illiterate. The percentage is much higher for complex questionnaires (Selltiz, Wrightsman, and Cook, 1976, p. 296). While this percentage may seem high at first glance, it may well be an underestimate in light of a recent report released by the Comptroller General of the United States (1975). According to the report in excess of 23 million American adults are functionally illiterate. Specifically, 39 million adults cannot compute their paychecks if they include overtime; 48 million adults cannot determine the correct amount of change from a purchase; 52 million adults cannot read

help wanted advertisements; 86 million adults cannot compute the gasoline consumption rate of a car; and so on.

In light of the above statistics, it is no wonder that research employing self report techniques is fraught with error. In regard to benefit segmentation specifically, the problem is that attribute elicitation techniques are not very useful for tapping a consumer's cognitive domain.

Considering all of the research conducted on segmentation, there is still a considerable need for improvement in isolating segments. It is believed that many of the existing problems can be overcome by the use of brand preference measures. Preference measures are more closely related to over behavior and thus more relevant to the purchase process. Also, they are more readily obtainable and not subject to the same type of errors as are attribute elicitation techniques.

CHAPTER III
METHODOLOGY

In light of the discussion presented in Chapter III concerning segmentation, it is apparent that previous research efforts aimed at isolating market segments have been less than successful. This is especially true for the earlier segmentation bases since the constructs they measure are so far removed from actual purchasing behavior. The product stream, on the other hand, is concerned directly with consumers' motivations in making purchase decisions and is more closely related to overt behavior. However, problems in measurement have prevented researchers (Wilkie, 1970; Mitchell, 1974; Anderson, Cox, and Fulcher, 1976) from achieving the promise of the product stream approach.

Some of these measurement problems can be eliminated by the use of certain kinds of psychometric procedures, which present a more unobtrusive method for achieving similar results. By focusing upon brand preferences, these psychometric procedures lead to segmentation results from which the attributes of the product class can be inferred with greater confidence.

Psychometric Scaling

A number of different techniques and algorithms have been developed by psychometricians for locating a complex stimulus along a number of dimensions simultaneously. These various techniques have been grouped under the name multidimensional scaling (MDS) and are concerned with two basic types of input data, either proximity measures or dominance measures (Coombs, 1950). Both of these approaches consist of a body of techniques for locating stimulus objects in a geometric space of minimum dimensionality which is representative of the respondent's cognitive structure.

A brand or product can be considered as composed of both objective and perceived attributes or dimensions. Such perceived attribute spaces consist of brand positions in relation to dimensions reflecting the consumer's perception of the product class. This perceptual space may vary over individual perceivers as well as over time and context within the same individual. Also, the dimensionality of the space may vary over stimulus object classes.

Nonetheless, for the purpose of consumer perception, the derived dimensions are the relevant ones. That is, the dimensions that are recovered are ones upon which the brands can be discriminated, and other dimensions on which the brands do not differ are not part of the solution.

Thus, MDS fulfills the requirements of deterministic attributes (Myers and Alpert, 1968) far more efficiently than attribute elicitation techniques. Such solution efficiencies are another advantage of MDS procedures over the attribute elicitation approach besides the decreased complexity of data gathering.

This study will deal with dominance data which provide a spatial configuration of the stimulus objects as well as a position for the individual generating the data. The axes' projections of this position are the individual's weights for the attributes underlying the product class. Thus the attributes as well as the importance an individual attaches to each for a product category are recovered.

Dominance Data

Under the domain of psychophysical measurement, dominance refers to the fact that one object possesses more of an attribute than does another. Thus, it can be said that one object is larger, louder, brighter, heavier, and so on; in short, it dominates the other on the characteristic of interest. In psychological processes though, dominance has primarily come to mean preference. Thus, there has been a development within psychometrics wherein the interest has been in uncovering the dimensions underlying preference.

It seems entirely reasonable that there should be a relationship between perception and preference. When asked to judge which object is preferred among a set, that judgment should be made in light of the dimensions which are used to discriminate the objects. The dimensions may be differentially important in judging preference, but the same basic dimensions should be used. Some support for this assumption has indeed been found (Green and Carmone, 1969; Carroll, 1972).

The dominance data concern pairs of objects which provide more evidence for constructing scales than when judgments are made on sets of more than two objects (Slater, 1960). Specifically, the element $P_{i(jk)}$ is the degree to which stimulus j is judged dominant over, or preferred to, stimulus k by individual i. A linear transformation of these preference strengths, the $P_{i(jk)}$, into descriptive scale values has been presented by Bechtel (1976). These scale values are least squares estimates of the parameters contained in the following orthogonal analysis of variance model:

$$P_{i(jk)} = S_{ij} - S_{ik} + U_{jk} + e_{ijk}$$

where:

$P_{i(jk)}$ = individual i's preference for object j over k

S_{ij} = individual i's scale value for object j

S_{ik} = individual i's scale value for object k

U_{jk} = unscalability associated with the pair j, k

e_{ijk} = random error

The individual scale values are tantamount to Thurstonean scale values (cf. Torgerson, 1958, pp. 169-173). The similarity between this model and the more familiar analysis of variance model is seen more clearly when one considers that S_{ij} and S_{ik} are analogous to main effects and that U_{jk} is analogous to an interaction term. Detailed procedures are outlined by Bechtel (1976) not only for estimating the parameters but also for determining their significance. That is, the sum of squares associated with each effect can be obtained and used to derive independent F tests of hypotheses of equality among various sets of parameters.

Besides the analysis of variance tests of significance, Bechtel (1976) also shows how indications of the reliability and validity of the scale values can be determined. In the statistical sense reliability refers to freedom from random error (Wells, 1975), and therefore the correlation between the $P_{i(jk)}$'s and the first three parameters in the above model are indicative of the reliability of the data. In a similar fashion, since the unscalability stems from systematic error the correlation between the $P_{i(jk)}$'s and the differences in the scale values indicate the degree of validity inherent in the data. Obviously, the validity coefficient has an upper bound at the reliability coefficient, this correspondence occurs when all of the unscalabilities are equal to zero.

The multidimensional model that has been advanced to deal with individual preference that is directly analogous to some attitude models (Rosenberg, 1956; Fishbein, 1967) is the vector model (Tucker, 1960; Slater, 1960). The vector model proposes that an individual's scale value for an object is the scalar product of the object's coordinates in the space and a vector of weights describing the differential importance of each dimension (plus some random error). That is:

$$S_{ij} = \sum_{r=i}^{t} O_{jr} I_{ir} = e_{ij}$$

where:

S_{ij} = individual i's scale value for object j

O_{jr} = the projection of object j on dimension r

I_{ir} = the importance of dimension r for person i

e_{ij} = random error

t = the number of dimensions

Inspection of the vector model indicates that it assumes preferences change monotonically with increments in the objects' position on the dimensions. That is, the more of an attribute any object possesses the higher its scale value. For those dimensions weighted negatively by an individual, the less of an attribute the object possesses the higher the scale value. The analogy with attitudes is apparent by noting that in reviewing the literature on multiattribute attitude models, Wilkie and Pessemier (1973) found that fully 21 of the 42 studies used preference as a surrogate for attitude.

The present study then is concerned with the development of a segmentation scheme using preference data obtained in a paired comparison format and comparing this procedure with benefit segmentation. The paired comparison format provides the best evidence for the internal consistancy of a scale (Slater, 1960). The use of preference data adds a motivational flavor to the representation of an individuals cognitive structure in line with the goals of the product stream and is more relevant for product choice processes (Wilkie and Pessemier, 1973).

In one sense, the brand preference segmentation scheme used here and the benefit segmentation procedure usually employed by researchers are related in that they are both concerned with identifying market segments that have similar behavioral patterns with respect to brand purchasing. Also, both deal with the importance individuals have for the attributes of a product class. In essence, the difference between the two procedures is really an issue of measurement. Researchers interested in benefit segmentation have focused on importance weights as the applicable measure. Specifically, Mitchell (1974) found that benefit segments based upon importance scores were more useful and interpretable than segments based upon affective scores.

Product Classes

Granted that segmentation is a useful management tool, it is not meant to be implied that segmentation is equally applicable to all products and markets. Indeed, many industrial and government markets which rely heavily on personal selling deal with such specifically defined markets that segmentation as a research strategy is superfluous. It is in the consumer package goods area that segmentation would seem to have its most advantageous use. In fact, this area has accounted for almost all of the segmentation literature since there is considerable uncertainty as to the optimum strategy to follow in marketing consumer package goods.

This uncertainty results from the characteristics of hetergeneous mass markets, frequent purchase, low price, and aggressive competition (Wilkie, 1970). Therefore, this study will be concerned with delineating segments for consumer package goods, although the techniques may well apply in other areas as well. Specifically, the study will deal with two product classes, analgesics and hard-surface floor cleaners. The analgesic class includes the following brands: Bayer, Bufferin, Anacin, Excedrin, Empirin, B.C., Tylenol, and Datril. The hard-surface floor cleaning class includes: Aero Wax, Glo Coat, Klear, Future, Step Saver, Mop & Glo, and Floor Shine.

These two product categories were selected for analysis for the following reasons. First, it is believed that housewives enjoy a certain amount of autonomy in choosing these products and are not limited by the influence of other family members. Thus, by employing psychometric procedures the resulting configuration should directly tap their cognitive domain. Secondly, the limited number of brands named above account for virtually the entire product category whereas many others meeting the first reason consist of a myriad number of brands. For instance, recent sales figures for the analgesic market show Tylenol to be the sales leader with 15.9% of the market; followed by Anacin with 13.7%, Bayer with 10.7%, Bufferin with 9.9%, Excedrin with 7.3%, and Datril with 1.8% (Giges, 1977). Thus, just these six brands alone account for 60% of the analgesic sales in this country. Therefore, the resulting product space configuration should include all of the respondents cognitive structure concerning the product class while requiring only a limited amount of input.

Objectives

The objectives of the study can be subsumed under three main areas of inquiry, which have been derived from the criteria for meaningful segmentation proposed in Chapter I.

In review, these criteria are:

1. Identification of homogeneous consumer groups.
2. Brand usage.
3. Sensitivity to marketing mix elements.

In practice, segmentation researchers have begun by isolating groups on the basis of one of the criteria and then testing to see if these groups also fulfill the other criteria. Early in the history of segmentation research groups were isolated with respect to the first criterion so as to be homogeneous in their demographic or personality characteristics and then examined for their fulfillment of the latter two. More recently there has been a tendency to start by isolating groups that have similar purchasing proclivities thereby fulfilling the second criterion, and then focusing on the two remaining ones. The point being, that efficiency is best served by beginning with segments that fulfill one of the criteria by definition and then examining them for their performance on the remaining ones.

Thus study will begin with the first criteria and identify homogeneous consumer groups. The benefit segmentation procedure will start with groups that are homogeneous with respect to their profile of importance ratings and the product segmentation will begin with groups that have similar scale value profiles. These two alternative methods will then be compared for their efficacy in achieving the other two criteria.

First, it is believed that the segments derived by the use of preference measures will exhibit more differential behavior with respect to brand usage than will the segments derived from the importance measures. This result is expected since, as discussed in Chapter I, preferences are more closely related to behavior.

Secondly, it is also believed that the preference segments will be more differentially responsive to elements of the marketing mix. This should result since preferences are less grounded to immutable intrapersonal characteristics and are partly determined by external sources. It is felt those individuals who have developed similar preferences have similar information gathering proclivities. Thus, these segments should provide greater stability in the sense that the segments will be more significantly different in their cognitive structure.

Also, the stimulus configurations developed by the psychometric procedures for each segment will be marked by solutions of lower dimensionality than would result from scaling all respondents into a common stimulus space. Thus, such a procedure will provide for not only differences in preference among the respondents but also differences in their perceptions of the product class. This procedure will be an improvement over the usual way of using MDS and will result in solutions which are of lower dimensionality, and

which are idiosyncratic to the segment. By focusing on fewer dimensions for each segment, clearer guidelines for strategy development will be available.

Lastly, while the segments are homogeneous with respect to their scale values and importance ratings, it is desired to see if they are identifiable in terms of some more readily available ancillary descriptors. Thus they will be tested to see if they can be identified by background demographic variables.

It should be kept clearly in mind that all of these objectives are united by the common thread of furnishing marketing management with a methodology for identifying market segments that will lead to the development and implementation of meaningful strategy. Obviously, a procedure which can do this efficiently and reliably is of great value.

Data Collection

Obviously, an undertaking of this magnitude will require a large amount of data. Accordingly, a two phase survey covering the two product categories will be conducted in order to investigate the above discussed objectives. The survey will consists of a non probability sample of housewives residing in the state of Florida. Housewives will be used since they will provide for more realism plus the fact that some other convenience sample

(e.g. students) may not be heterogeneous enough to exhibit distinct segments.

Accordingly, phase one will consist of a pretest to elicit attributes salient to the purchase of analgesics and hard-surface floor cleaners (see Appendix A). Such a procedure is standard in the social sciences for obtaining the attributes of an object. It is assumed that beliefs about an object can be elicited in a free-response format by asking respondents to list the characteristics, qualities, and attributes of the object. It has been argued that salient beliefs are elicited first, and, thus, those elicited beyond the first nine or ten are probably not salient for the individual. As a rule of thumb then, it has been recommended to use the first five to nine attributes (Fishbein, 1967).

The main emphasis is in the second phase where five different types of data will be collected for each product category. Measures will be obtained of each respondent's (1) brand preferences in the paired comparison format, (2) importance ratings for the product attributes, (3) product usage, (4) sensitivity to marketing mix elements, and (5) background demographic data (see Appendix B).

The paired comparison brand preferences are, of course, the usual input for MDS procedures as outlined above, these are presented in randomized order according to the procedure outlined by David (1963) in order to prevent response bias. The importance ratings are for the attributes obtained in

phase one. The product usage data refer to the brand usually purchased, the degree of brand loyalty, and the amount of the product used. The background demographic data consist of the following measures: the respondent's age, marital status, race, religion, number of children living at home, number of children under six, education, employment, occupation of the household head, household income, and dwelling status.

The key area of sensitivity to marketing mix elements will be patterned after the price, distribution, and promotion variables. The price variables include the increase required to induce brand switching, an index of dealing, and coupon usage. The type of retail outlet purchases are made at and an index of store loyalty are the distribution variables. The promotional variables include the newspapers and magazines read plus the time spent reading them as well as the type of radio and television programing attended to and the amount of time spent in these pursuits. Also included is an index of personal communication regarding product categories.

Analysis

In order to define segments and compare procedures for their efficacy in fulfilling the criteria of meaningful segmentation there need to be several waves of data analysis. Figure 3 presents the plan of analysis in flow

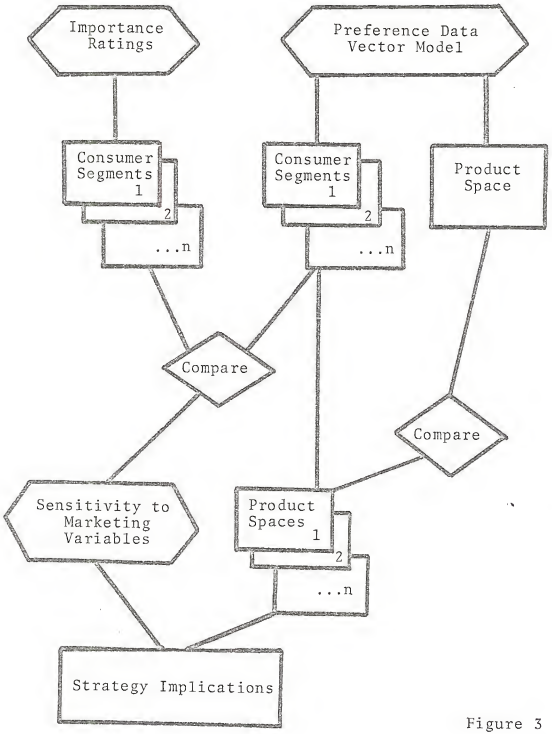

Figure 3

PLAN OF ANALYSIS

chart form and should prove helpful in conceptualizing the research. All of the steps outlined below will, of course, be carried out twice, once for each product category.

The first task will be to identify the benefit and preference segments. This will be accomplished by submitting the importance ratings and the unidimensional scales derived from the paired comparison data to inverse factor analysis, or Q analysis, for clustering purposes. Since the emphasis is on the profile of the scales, the covariance between individuals as employed in Q analysis should provide good results.

Specifically, the technique used is principal component analysis followed by varimax rotation. Rather than use the raw factor loadings, each respondent's loading on a factor will be indexed to the average loading for that factor. Due to the fact that some loadings are negative, ordinary arithmetic averages are not used, but rather the square root of the average squared value for each factor. Each respondent is then allocated to the group where she has the highest index, even though she may have a higher loading with some other factor. These "normalized Q groups" tend to produce results that are more reliable when the analysis is repeated with new data (Johnson, 1974).

After obtaining the segments formed by the two approaches, they will be compared by relating them to the product usage data and the marketing mix measures. First, crosstabulation of the groups with the nominally scaled data and analysis of variance with the ration scaled data will highlight on which particular variables the groups are significantly different. Secondly, the statistically significant variables will be used as independent variables in a discriminant function which takes into account the covariation between variables to predict segment membership in order to assess which of the segmentation approaches is more highly associated with the other variables.

A discriminant function will also be run using the demographic measures as independent variables. This will be done in order to determine if the groups are identifiable in terms of these ancillary variables.

Next, the vector model will be used for deriving a spatial representation containing both brand positions and individual importance weight vectors for the entire sample. Then, each of the preference segments will be scaled by the vector model to provide separate spaces for each. This will enable a comparison of these spaces with the common space and it should turn out that the segment spaces are of lower dimensionality and are idiosyncratic to each segment.

By focusing on the spatial configurations, the univariate results, and the discriminant function

concurrently the issue of segment interpretability can be addressed. By noting the determinant attributes and the significant independent variables, meaningful segmentation guidelines can be formulated for each segment. These guidelines will consist of both strategy plans and the tactics for implementing them.

CHAPTER IV
RESULTS AND DISCUSSION

In the first phase of the analysis a sample of 50 housewives was asked to elicit in an unstructured format (see Appendix A) specific attributes that they take into consideration when purchasing analgesics and hard-surface floor cleaners. The 28 attributes which were mentioned for analgesics along with the number of respondents mentioning them are presented in Table 1. It was decided to use those attributes which were mentioned by 10% or more of the sample in the phase two questionnaire. Thus, the attributes rated for importance in the main portion of the study included:

- effectiveness in eliminating pain
- cost/price
- doesn't upset the stomach
- fast acting
- doesn't cause side effects
- recommendation of your doctor
- works on different types of pain
- package size
- chemical ingredients
- reputation of the brand name

Table 2 lists the 25 attributes mentioned for hard-surface floor cleaners and the number of respondents mentioning each. Using the same 10% or more criterion it was decided to include the following 11 attributes in the phase two questionnaire:

Table 1

Frequency of Elicited Attributes
for Analgesics

Attribute	Number of Subjects	Percentage
Effectiveness in eliminating pain	32	64
Cost/Price	32	64
Doesn't upset the stomach	20	40
Fast acting	19	38
Doesn't cause side effects	10	20
Recommendation of doctor	8	16
Works on different types of pain	8	16
Package size	7	14
Chemical ingredients	7	14
Reputation of brand name	5	10
Strength	4	8
Time between doses	4	8
Recommendation of friends	3	6
Past experience	3	6
Suitability for all ages	3	6
Ease of swallowing	2	4
Taste	2	4
Dosage amount	2	4
Advertising image	2	4
Compatible with other drugs	1	2
Non-habit forming	1	2

Table 1 - continued

Attribute	Number of Subjects	Percentage
Effects with alcohol	1	2
Daytime or nightime use	1	2
Family preference	1	2
Child proof container	1	2
Consumer Reports evaluation	1	2
Prior medical tests	1	2
Shelf life	1	2

Table 2

Frequency of Elicited Attributes
for Hard-Surface Floor Cleaners

Attributes	Number of Subjects	Percentage
Cost/Price	34	68
Ease of application	28	56
Cleaning effectiveness	21	42
Removes old wax	15	30
Long lasting shine	15	30
Non-yellowing shine	15	30
Quick drying	9	18
Resists scuffing	8	16
Can be used for many floor types	5	10
Fragrance	5	10
Shines after mopping	5	10
Package size	4	8
Safe to use around children and pets	4	8
Ingredients	3	6
Reputation of brand name	3	6
Recommendation of friends	3	6
Non-stickiness	2	4
Application amount	2	4
Past experience	2	4
Guaranty	1	2
Advertising claims	1	2
Consumer Reports evaluation	1	2

Table 2 - continued

Attributes	Number of Subjects	Percentage
Impervious to water	1	2
Other equiptment needed	1	2
Non-slippery	1	2

·cost/price
·ease of application
·cleaning effectiveness
·removes old wax
·long lasting shine
·non-yellowing shine
·quick drying
·resists scuffing
·can be used for many floor types
·fragrance
·shines after mopping

A random number table was used to determine the order that both of these attribute lists appear in the phase two questionnaire in order to prevent biasedness in responding.

The above task having been completed, the phase two questionnaire was administered to 35 individuals for pretesting. Analysis of these results enabled the questionnaire to be rephrased in a number of places so as to provide for greater clarity. Once this had been accomplished, the final questionnaire (see Appendix B) was administered to 218 housewives throughout the state of Florida. These women were contacted through various religious, social, and civic organizations which received $2 for each participant competing a questionnaire. Since this is a convenience sample, it is not representative of the nation's housewives. For example, there are more whites and catholics with higher incomes, more education, and fewer children among the respondents than found in the general population.

Preliminary inspection of the questionnaires indicated the 19 of them were so full of errors and ambiguous as to be totally useless for any purpose. These were immediately eliminated and the remainding 199 respondents comprised the sample for the study. While many of these questionnaires

were incomplete and thus there is much missing data, it was felt that enough information was present to provide for meaningful analyses. The data are concerned with two product categories and each will be analyzed in turn.

Analgesics

The analgesic market will be analyzed with the three criteria for meaningful segmentation developed in Chapter I firmly in mind. Thus the concern is with the issues of identification of segments, brand usage, and sensitivity to marketing mix elements. Since these derive the main areas of investigation outlined in Chapter III, the analysis should provide an indication of the more efficient segmentation procedure for isolating segments which provide for more meaningful strategy development.

Identification and Usage

The first task to be undertaken in order to address the first objective is to determine the various segments of the analgesic market. Accordingly, each subject's importance ratings for the 10 analgesic attributes were submitted to inverse factor analysis, or Q analysis, since the emphasis is on identifying consumers who have similar profiles, or utility, for the various attributes.

Three of the respondents had given the same importance weight for all 10 attributes and thus their profile was a constant with no variance and they were eliminated from the

analysis. Inspection of the eigenvalues (see Appendix C) associated with the remaining subject's correlation matrix indicated that 6 factors should be retained which explain 89.6% of the variance in the original data. The loadings on the 6 factors were submitted to varimax rotation and each respondent's loadings was indexed to the average loading for that factor according to the procedure developed by Johnson (1974) outlined in Chapter III. Assignment of each subject to the factor where she has the highest index resulted in 38 individuals being allocated to group 1, 37 to group 2, 37 to group 3, 25 to group 4, 28 to group 5, and 31 to group 6.

Analysis of each group's mean rating on the 10 attributes presented in Table 3 indicates that the brand's effectiveness in relieving pain and its lack of unwanted side effects are primarily important to the entire sample. However, the relative importance they place on other attributes differs. Group 1 seems to be more interested in price, ingredients, a doctor's recommendation, reputation, and causation of stomach upset while being less concerned about a generalized pain reliever and speed of action. The speed of relief provided is relatively more important to group 2 whereas a generalized pain reliever and a doctor's recommendation are of very little importance. Group 3 has more interest in a generalized pain reliever, ingredients, and causation of upset stomach but unconcerned about the brand's reputation. The package size and stomach

Table 3

Mean Attribute Rating for
Analgesic Importance Groups

Attribute	Group 1	2	3	4	5	6
Effectiveness	6.61	6.97	6.86	6.72	6.93	6.68
Price	4.79	3.81	4.22	4.16	3.68	2.39
Different types of pain	3.66	4.73	5.78	5.12	5.50	5.74
Chemical ingredients	6.32	3.11	6.19	4.44	3.39	5.84
Doctor's recommendation	6.39	3.54	5.84	5.92	6.54	6.13
Brand reputation	4.97	4.22	2.43	4.48	4.75	5.87
Side effects	6.58	6.24	6.59	6.52	6.14	6.39
Fast acting	5.50	6.24	5.73	5.84	5.71	5.77
Package size	2.71	2.54	3.24	4.04	1.82	2.61
Doesn't upset stomach	6.16	5.67	6.11	6.12	4.14	5.93

upset effects are of more interest to group 4 while price is not. Group 5 is more concerned about a doctor's recommendation and less concerned about the package size and causation of side effects. Group 6 is more interested in a doctor's recommendation and reputation of a generalized pain reliever but doesn't care about price.

The assumption underlying this segmentation procedure is that consumers who desire similar attributes in a product will buy the same brand. Therefore, since the above groups have been identified in this manner it would be expected that each group purchase the same brand and that different groups purchase different brands. However, comparison of the individual members of each group with the brand they most frequently purchase indicates that this is not true. A crosstabulation of this data is presented in Table 4 which indicates that the groups are not significantly different in their brand purchasing. Inspection of Table 4 discloses that there are a number of cells with very low expected frequencies and that a chi-square statistic may be inappropriate in this case. In order to correct for this deficiency a number of the rows were combined. Specifically, the Anacin, B.C., Bufferin, Empirin, and Excedrin rows were combined as well as the Datril and Tylenol rows. Thus, there are now 6 groups times only 4 rows: Bayer, aspirin containing brands, non aspirin brands, and other brands. As shown, crosstabulation produces a highly non significant chi-square and thus the hypothesis of independence can not be rejected.

Table 4

Crosstabulation of Analgesic Importance Groups with Brand Purchased

	Group					
Brand	1	2	3	4	5	6
Anacin	5	2	3	3	0	4
Bayer	5	9	9	3	8	9
B.C.	0	0	1	0	0	0
Bufferin	6	2	1	3	0	2
Datril	1	0	1	2	2	0
Empirin	1	1	1	0	1	1
Excedrin	2	5	2	1	5	3
Tylenol	12	11	12	10	9	8
Other	6	7	7	3	3	4

Chi-Square = 9.901*

DF = 15*

Probability = 0.8088*

* based upon a contingency table having combined rows (see text)

The identification of segments based upon their paired comparison preferences is slightly more involved. Initially the variance contained in the paired comparisons needs to be partitioned in the analysis of variance format discussed in Chapter III to determine the significance of the individual's scale values. This analysis of variance is presented in Table 5 which shows that the scale values are highly significant. While the F test for the unscalability is also significant due to the large degrees of freedom, analysis of the sum of squares column shows that 82.2% of the variance is accounted for by the scale values whereas only 0.3% of the variance is accounted for by the unscalability. Futhermore, the overall validity correlation coefficient between the original preferences and the scale values is .906 while the reliability correlation coefficient between the original preferences and the scale values plus the unscalability is .907, also indicating that the data is relatively free of systematic and random error. Thus, the data is highly reliable and possesses a high degree of internal validity which bodes usefulness for multidimensional scaling. However, partitioning of the sum of squares attributable to the scale values into orthogonal components for each subject obtains 5 non significant F's at an alpha level of .05. This indicates that their scale values are not significantly different from zero and thus they are indifferent to the analgesic brands. Further support is provided in that the average validity correlation coefficient between the original

Table 5

ANOVA for Analgesic Preferences

Source	SS	DF	MS	F
Scales	58978.000	1393	42.339	14.002*
Unscalability	189.456	21	9.022	2.984*
Error	12572.544	4158	3.024	
Total	71740.000	5572		

*probability > .001

preferences and the scale values for these 5 subjects is a lowered .812. These indifferent subjects were, therefore, deleted from further analysis.

The remaining 194 respondents were submitted to the same factor analytic procedure as outlined above. In this case the correlation between individual profiles was based upon the scale values for eight brands which sum to zero and thus the correlation matrix has only 7 non zero eigenvalues (see Appendix C). Thus, retaining all seven factors will explain 100% of the variance in the scale values. It was deemed appropriate to do this for two reasons. First, all of the variance can be explained by using a relatively small number of groups roughly equal to the number of importance rating groups. Second, it is felt that each brand has some cadre of loyal buyers who should be considered as a segment.

Assignment of each subject to the factor where she has the highest index resulted in 38 individuals being allocated to group 1, 34 to group 2, 22 to group 3, 25 to group 4, 24 to group 5, 24 to group 6, and 27 to group 7. The average scale value for each group is shown in Table 6.

While it was shown above that the groups based upon importance ratings did not purchase significantly different brands, a similar analysis of the preference groups shows that these groups do have significantly different purchasing proclivities. A crosstabulation of the preference groups with the brand they most frequently purchase is presented in

Table 6

Mean Scale Values for
Analgesic Preference Groups

Brand	Group 1	2	3	4	5	6	7
Anancin	-1.00	-0.16	1.72	-0.74	-0.51	2.13	-0.94
Bayer	-0.00	3.74	0.45	1.34	0.27	1.32	0.34
B.C.	-2.37	-1.53	-1.77	-1.68	-2.48	-1.66	-1.33
Bufferin	-0.40	0.42	0.41	3.08	-0.55	0.26	0.52
Datril	2.48	-1.43	-1.70	-1.22	-1.43	-1.54	-1.70
Empirin	-1.27	-1.44	-1.23	-0.62	2.36	-0.99	-1.49
Excedrin	-0.61	0.07	2.69	-0.81	0.53	-0.21	0.75
Tylenol	3.18	0.33	-0.57	0.65	1.82	0.70	3.85

Table 7. Inspection of this table reveals that a number of the cells have very low expected frequencies and thus the chi-squares statistic may not be appropriate. In order to correct for this deficiency a number of the rows were combined. Specifically, the Anacin, B.C., Bufferin, Empirin, and Excedrin rows were again combined as well as the Datril and Tylenol rows. Thus there are now 7 groups times only 4 rows: Bayer, aspirin containing brands, non aspirin brands, and other brands. Crosstabulation now produces a highly significant chi-square indicating that the procedure using preferences as the segmentation input produces more meaningful segments with regard to brand purchasing behavior as would be expected.

Marketing Mix Elements

Before further inquiry into the differential behavior of the groups formed using the two types of data it is appropriate to insure that the two procedures do in fact result in different groupings of the subjects. Towards this end the crosstabulation presented in Table 8 indicates that while the two grouping methods are not independent the relationship between them is rather weak as evidenced by the low Cramer's V statistic. Thus, it is clear that these two methods result in very different segments.

Having satisfied this point, the next step is to ascertain the association between the groups and the various

Table 7

Crosstabulation of Analgesic Preference Groups with Brand Purchased

	Group						
Brand	1	2	3	4	5	6	7
Anacin	0	0	7	0	1	9	0
Bayer	4	22	1	8	2	4	3
B.C.	0	0	0	0	1	0	0
Bufferin	0	0	0	13	0	0	0
Datril	6	0	0	0	0	0	0
Empirin	0	0	1	0	4	0	0
Excedrin	1	0	7	0	3	4	3
Tylenol	20	3	3	2	12	5	18
Other	7	9	3	2	1	2	3

Chi-Square = 127.258*

DF = 18*

Probability = 0.001*

* based on a contingency table having combined rows (see text)

Table 8

Crosstabulation of Analgesic Importance Groups with Preference Groups

Preference Group	Importance Group					
	1	2	3	4	5	6
1	5	5	9	9	7	3
2	6	6	2	1	6	13
3	1	8	1	4	2	5
4	8	3	6	4	2	2
5	4	7	4	1	5	3
6	8	2	7	4	2	1
7	6	5	6	1	4	3

Cramer's V = 0.238

marketing mix elements. There are 35 variables dealing with price, distribution, and promotional issues as outlined in Chapter III. Of these, two, the type of store where subjects usually purchase analgesics and the place they usually listen to the radio, were eliminated due to the fact that such a large number of the sample, 57% and 21% respectively, failed to answer these questions.

Importance groups. Of the remaining 33 variables, 8 consist of ratio scaled data and 25 are binary zero/one indicating whether or not a subject reads a particular type of magazine, listens to a particular type of radio program, or watches a particular type of television program.

The importance groups were then tested to see if there were differences between group means on these variables. Crosstabulations were run on the discrete variables while analysis of variance was performed on the ten continuous variables. The significance levels for the resulting chi-square and F statistics are presented in Table 9. It can be seen that at an alpha level of .10 the importance group means are significantly different on only six of the variables:

- percent of time the brand is used
- listening to popular radio programs
- listening to news/weather radio programs
- watching action television programs
- watching talk show television programs
- time watching television programs

These results, being univariate in nature, do not take into consideration the covariance structure in characterizing

Table 9

Significance of the Analgesic Importance Group Means on the Marketing Mix Variables

Variable	Probability Level
Percent of time brand used	.0288**
Amount used	.4695
Buy at the same store	.3167
Price increase for switching	.3841
Check ads for sales	.4736
Clip and use coupons	.7226
Number of newspapers read	.5146
Time reading newspapers	.7008
Magazine type readership	
Beauty/Fashion	.2802
News	.1657
Sports	.3954
Home/Garden	.8901
Movie	.7307
Hobby	.2088
General Interest	.4245
Time reading magazines	.1024
Radio program listening	
Popular	.0010***
Easy listening	.1342
Classical	.1980

Table 9 - continued

Variable	Probability Level
News/Weather	.0633*
Talk show	.3505
Time listening to radio	.2405
Radio frequency	.4267
Television program watching	
News/Weather	.1071
Sporting events	.8385
Movies	.1464
Action	.0052***
Comedy	.1783
Variety	.1702
Game shows	.6593
Talk shows	.0345**
Time watching television	.0491**
Consulting with others	.6101

* p>.10

** p>.05

*** p>.01

the groups and for this reason multiple discriminant analysis was used to see what effect the covariation would have on the results. Linear discriminant analysis if a natural technique to use when the data consist of a categorical criterion variable and a set of possible predictor variables. This technique involves certain assumptions about the form of the data which are not true in this case and will be discussed below. Still, application of this technique can provide useful insights into the relationship between group membership and marketing mix elements.

The variables were submitted to the SPSS stepwise discriminant procedure to determine which variables are most able to discriminate among the importance groups. The criterion used for inclusion into the model is the largest increase in the generalized distance as measured by Rao's V. The variable which contributes the largest increase in V when added to the previous variables is the one selected for inclusion into the model. This amounts to the largest overall separation between the groups. The change in V is distributed as a chi-square with g-1 degrees of freedom, where g equals the number of groups, and so can be tested for significance. An alpha level of .10 was chosen as the cutoff point and 6 variables were found to contribute to the classification model. These variables are:

- listening to popular radio programs
- watching action television programs
- percent of the time brand is used
- watching talk show television programs
- time reading magazines
- time watching television programs

Five of these variables are the same as univariate results with the time reading magazines as the new addition. These variables were then used to discriminate the importance group membership. Since a few of these variables contain missing data, these observations are deleted from the analysis and the size of the sample shrunk to 193 from the original 196. Of these, the model correctly classified 66 of the observations as shown in Table 10, a score of 34.2%

This statistic by itself does not indicate the classificatory power of the model in uncovering structure. To address this issue, Montgomery (1975) has devised a procedure to assess the expected spurious percent of correct classifications. His procedure involves random assignment of each actual observation to the segments in proportion to the observed sample incidence of these groups. By running a discriminant analysis with the actual observations in these randomized segments a base line for spurious performance is obtained.

Accordingly, three of these randomized discriminant runs were undertaken and they classified 54, 55, and 64 observations correctly; scores of 28.0%, 28.5%, and 33.2% respectively. Thus, on the average predictability is

Table 10

Classification Matrix for Analgesic Importance Groups Using Marketing Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	17	3	11	2	1	4
2	3	19	7	1	3	4
3	13	6	10	2	4	1
4	6	5	5	4	1	4
5	4	6	6	2	7	2
6	11	6	1	2	1	9

Total number = 193

Number correct = 66

Percent correct = 34.2%

increased only 4.3% by placing the observations in the proper segments.

Preference groups. A similar process was undertaken using the same variables to discriminate among the preference groups. First, univariate tests were performed to determine on which variables the preference groups differed. The significance levels for the variables are presented in Table 11 and it can be seen that the preference group means differ on only 7 variables. These are:

- amount used
- time reading newspapers
- reading general interest magazines
- listening to popular radio programs
- listening to talk show radio programs
- watching variety television programs
- watching game show programs

Again, in order to take into consideration the effect of the covariance between variables, multiple discriminant analysis was employed. While the problem of violation of the assumptions of the model still exists (see below), it is not believed to have serious impact on the implications of the results.

The stepwise procedure using the change in Rao's V as the criterion was again used. At an alpha level of .10, it was found that 5 variables were significant. These are:

Table 11

Significance of the Analgesic Preference Group Means on the Marketing Mix Variables

Variable	Probability Level
Percent of the time brand used	.4450
Amount used	.0002***
Buy at the same store	.7735
Price increase for switching	.5019
Check ads for sales	.7083
Clip and use coupons	.3966
Number of newspapers read	.3361
Time reading newspapers	.0283**
Magazine type readership	
Beauty/Fashion	.1526
News	.5103
Sports	.8842
Home/Garden	.2559
Movie	.4909
Hobby	.5474
General Interest	.0585*
Time reading magazines	.4487
Radio program listening	
Popular	.0674*
Easy listening	.4103
Classical	.5756

Table 11 - continued

Variable	Probability Level
News/Weather	.4821
Talk show	.0198**
Time listening to radio	.5308
Radio frequency	.5589
Television program watching	
News/Weather	.4406
Sporting events	.3484
Movies	.5615
Action	.6877
Comedy	.8047
Variety	.0894*
Game shows	.0578*
Talk shows	.2278
Time watching television	.5055
Consultation with others	.3153

* p>.10

** p>.05

*** p>.01

·amount used
·listening to talk show radio programs
·reading beauty/fashion magazines
·listening to popular radio programs
·time reading newspapers

Four of these variables are the same as were found in the univariate analysis with readership of beauty/fashion magazines being the new addition. These variables were then used to discriminate the preference groups. Again, of course, a few of the variables contain missing data and the number of observations retained drops to 187 from the original 194. This model though classified 56, or 29.9%, of the observations correctly as shown in Table 12.

While the percent classified correctly is lower for the preference groups than for the importance groups, it must be remembered that there is an extra group to be classified with one less variable. For this reason, the Montgomery (1975) procedure was employed to assess the improvement this model provides over spuriousness. Accordingly, three randomized discriminant runs were undertaken which classified 42, 44, and 44 observations correctly; 22.5%, 23.5%, and 23.5% respectively. Thus, placing the observations in the proper segments improves predictability by 6.7% on the average.

Since the significant variables tend to be a small subset of the original 33, it was decided to see if the addition of more variables would increase the performance of the discriminant function. The stepwize procedure was used specifying a multivariate partial F test on the mean

Table 12

Classification Matrix for Analgesic Preference Groups Using Marketing Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	21	11	0	0	2	0	3
2	10	20	0	0	0	3	1
3	7	5	1	0	0	6	2
4	8	7	2	1	0	5	1
5	11	6	0	0	2	1	3
6	4	5	3	2	1	4	3
7	6	8	1	1	3	0	7

Total number = 187

Number correct = 57

Percent correct = 29.9%

difference between groups as the criterion. An F of 1.0 was chosen as the cutoff point and 13 variables were found to contribute to the importance group classifications and 19 variables contributed to the preference group classifications.

For the importance groups the 13 variables classified 42.9% correctly. Three randomized runs produced correct classifications of 36.5%, 38.5%, and 39.8%. Thus, on the average the real importance groups increase predictability over spuriousness by 4.6%.

The 19 variables classified 54.3% of the preference groups correctly. Correct classifications produced by the randomized process were 40.7%, 42.6%, and 43.2%. Here the increase in predictability amounts to 12.1% by using the real preference groups.

Demographics. In order to determine if the groups can be characterized by more readily available ancillary data, an attempt was made to discriminate the groups on the basis of 11 demographic variables. Five of the variables, age, number of children, number of children under 6 years of age, education completed in years, and income, are ratio scaled. Two others, employment and dwelling ownership, are binary zero/one. The remaining four, marital status, race, religion, and occupation of the household head, are nominally scaled and hence crosstabulations were run to determine if any of the groups differed on these variables. Crosstabulation of the importance groups with

the above four variables produced chi-square values of 20.569, 12.653, 14.986, and 24.373 respectively. At the associated degrees of freedom none of these statistics is significant above the .24 alpha level and thus all of these were deleted from the analysis.

Crosstabulating the same four variables with the preference groups produced chi-square values of 29.214, 13.151, 24.546, and 39.059 respectively. At the associated degrees of freedom none of these statistics is significant beyond the .21 alpha level so again these variables were deleted from the analysis. The remaining seven variables were then used attempting to discriminate the two types of groups.

The results for the importance groups appear in Table 13 which shows that use of these variables correctly classifies 28.2% of the observations. This model, considering the above results, is not very useful for characterizing the membership of the various groups. It should also be pointed out that while all of the variables were used, only one, age, was significant at the .10 alpha level according to the change in Rao's V criterion.

Table 14 contains the results for the preference groups which shows that use of these demographic variables classifies 29.4% of the observations correctly. Again, these results are not very useful for identifying segment members, especially since, according to the change in Rao's V criterion, none of the variables are significant at the

Table 13

Classification Matrix for Analgesic Importance Groups Using Demographic Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	13	4	6	1	4	4
2	2	15	8	0	8	3
3	6	14	7	0	3	6
4	6	9	3	1	3	2
5	1	7	5	0	9	2
6	7	4	9	1	2	6

Total number = 181

Number correct = 51

Percent correct = 28.2%

Table 14

Classification Matrix for Analgesic Preference Groups Using Demographic Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	24	3	2	2	0	3	3
2	15	6	0	5	1	3	2
3	8	0	4	2	1	2	2
4	9	1	1	7	0	2	0
5	12	4	3	0	0	4	1
6	9	2	1	2	0	7	0
7	9	2	3	0	2	4	4

Total number = 177

Number correct = 52

Percent correct = 29.4%

.10 alpha level. It seems then that the groups are not significantly different and can not be predicted at more than spurious levels by demographic variables.

Before leaving this section two caveats are in order. First, linear functions provide the best discrimination when the group covariance matrices of the independent variables are equal. Testing indicates that this is not true for this sample when using the small subsets of variables. For the results of an analysis using a quadratic function see Appendix D.

Second, inferences employing F statistics involve an assumption of multivariate normality among the independent variables. The use of binary variables in this study clearly violate this. Therefore, the results of these discriminant analysis should not be considered as absolutely conclusive in their own right. Still, violation of the assumptions or not, the results of the preceding section provide useful insights that are somewhat greater than spurious performance.

Marketing Implications

Addressing the final issue requires initially determining the dimensionality of the common product space which is representative of all the subjects' perceptual structure. This can be accomplished by inspection of the eigenvalues derived from the matrix obtained by premultiplying the subjects' scale value matrix by its transpose.

The eigenvalues are listed in Table 15 and plotted in Figure 4. There are 7 non zero eigenvalues since the analgesic scale values sum to zero. Inspection of the eigenvalues suggests retaining 4 dimensions.

This conclusion is confirmed by referring to Table 5 in conjunction with Table 15. It can be seen that the first 4 eigenvalues account for 78.2% of the variance in the scale value; that is, the sum of the squares attributable to the 4 dimensions is 46167.312. Thus, the sum of squares associated with the unused eigenvalues equals 12810.688 or 21.8% of the variance in the scales. Comparison of this figure with the error sum of squares indicates that the error increment in fitting a 4 dimensional submodel to the data is not excessive.

Obviously it is impossible to graphically display 4 dimensions so the coordinates of the analgesic brands are presented in Table 16. Inspection of this table can provide one with an appreciation of the difficulty involved in interpreting solutions of this dimensionality. It would appear from the fact that most subjects have a negative weight for this dimension coupled with the preponderance of Tylenol users in the sample (see Table 6) that dimension 1 is an evaluative dimension concerned with the analgesic's effectiveness in relieving pain. Inspection of the brand order on dimension 2 indicates that this dimension represents aspirin content. The last two dimensions, however, are much more arcane. They most probably represent

Table 15

Eigenvalues Obtained from
Analgesic Scale Values

Number	Value	Percent	Cumulative
1	2252.518	.306	.306
2	1832.105	.249	.555
3	1022.958	.139	.694
4	650.442	.088	.782
5	634.847	.086	.868
6	523.912	.071	.939
7	439.000	.060	1.000
8	0.000	.000	1.000

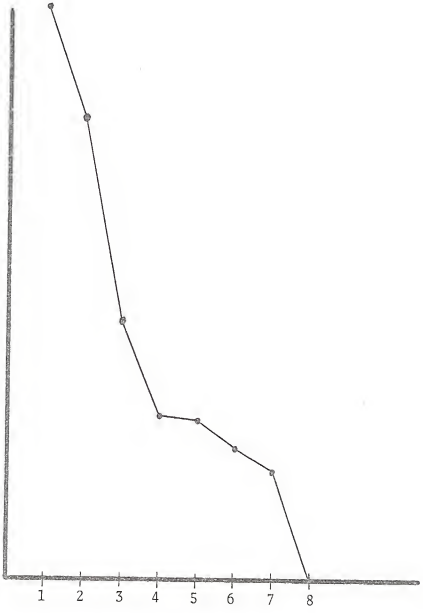

Figure 4

Eigenvalues Derived from
Analgesic Scale Values

Table 16

Coordinates of the Analgesic Brands
in the Common Product Space

Brand	Dimension 1	2	3	4
Anacin	0.136	0.255	-0.192	-0.324
Bayer	-0.301	0.504	0.392	-0.487
B.C.	0.566	-0.100	0.365	0.183
Bufferin	-0.104	0.317	0.241	0.726
Datril	0.059	-0.610	0.283	-0.262
Empirin	0.271	-0.140	-0.332	-0.046
Excedrin	0.064	0.163	-0.645	0.057
Tylenol	-0.692	-0.390	-0.111	0.153

some subjective aspects of the product class which can not be inferred without ancillary information.

While it requires 4 dimensions to represent the perceptual structure of all the subjects, this product space may not in fact be representative of any one subject but rather be generalizeable to some non existent average group member. This situation might well be improved by developing a product space for various segments of the market. This has usually been accomplished by segmenting on some a priori demographic variable and the results have been somewhat less than easily interpretable. It would seem to make much more sense to isolate segments on the basis of their similarity in preferences. In this way, the product space derived, since it contains the perceptual structure of subjects with similar preference, will result in solutions of lower dimensionality which are more easily interpretable.

Accordingly, each preference group identified above was submitted to a separate vector submodel analysis. While there is no longer a relevant error sum of squares for comparison, inspection of the eigenvalues for group 1 (see Appendix C) shows that 73.1% of the variance in the scale values is explained by the first dimension and that the remaining dimensions contribute a negligible amount in explaining the variance. Thus, the common product space for the individuals in group 1 is unidimensional in nature and is shown in Figure 5. It appears from inspection of

Figure 5

Product Space for Analgesic
Preference Group 1

the brand positions in the space that this dimension is concerned with aspirin content. Of the 38 subjects in group 1, fully 36 of them have high negative weight for this dimension indicating that this segment of the market is primarily interested in a non aspirin pain reliever. Based on the brand positions it would be expected that this group would be composed primarily of Tylenol users followed by users of Datril. This expectation is substantiated by referring to Table 7 which shows that in fact members of group 1 purchase these very brands most often.

The implication of this is that penetration of this segment is accomplished most efficiently by product development and promotional strategies which emphasize the non aspirin nature of the analgesic. Useful insights can be gained from Table 17 which list the preference group means for the variables found to significantly discriminate the variables in the previous section. It should be noted that the heavy users of analgesics, group 3 and group 6, are comprised primarily of Anacin and Excedrin users.

Tactically, group 1 tends to be light users of analgesics and spend a moderate amount of time reading newspapers. They are moderate readers of general interest magazines but light readers of beauty/fashion magazines. They are the heaviest listeners of popular programs but the lightest listeners of talk shows on radio. Also, they watch a moderate amount of variety shows but are the lightest watchers of game shows on television.

Table 17

Analgesic Preference Group Means
for Significant Marketing Variables

Variable	Group 1	2	3	4	5	6	7
Amount used	27.00	31.74	60.05	44.33	24.22	71.68	26.58
Newspaper time	4.27	3.14	4.38	4.54	6.04	6.36	5.04
General interest magazines	0.55	0.53	0.54	0.68	0.33	0.75	0.70
Beauty/Fashion magazines	0.27	0.44	0.43	0.25	0.43	0.41	0.62
Popular radio	0.65	0.32	0.43	0.33	0.52	0.27	0.50
Talk show radio	0.03	0.05	0.24	0.17	0.09	0.27	0.27
Variety television	0.32	0.41	0.14	0.24	0.25	0.38	0.52
Game show television	0.13	0.15	0.27	0.20	0.21	0.46	0.33

The product space for group 2 can be represented by 2 dimensions which account for 81.8% of the variance in the scale values (see Appendix C) and is depicted in Figure 6. Here the horizontal dimension seems to represent generalized evaluation since it is closely related to the scale values and acts like a first principle component. The vertical dimension represents aspirin content. Inspection of the vectors corresponding to the subject's importance weights for each dimension leads to the expectation that this segment should primarily consist of Bayer users and a few preferring Tylenol. Reference to Table 7 shows that this is the case.

Positioning strategy with respect to this segment should focus on competing with Bayer and be relatively neutral with respect to the aspirin content. Reference to Table 17 indicates that this segment tends to be light users of analgesics and spend the least amount of time reading newspapers. They are moderate readers of both general interest and beauty/fashion magazines. When listening to the radio they tend to be low on both popular and talk show programs. Finally, they watch variety programs on television moderately but watch game shows the least.

Group 3 can also be represented by a two-dimensional space which accounts for 74.4% of the variance (see Appendix C) and is presented in Figure 7. The horizontal dimension can be interpreted as strength and effectiveness whereas the vertical dimension seems to deal with safety and the absence of unwanted side effects. The importance weight vectors

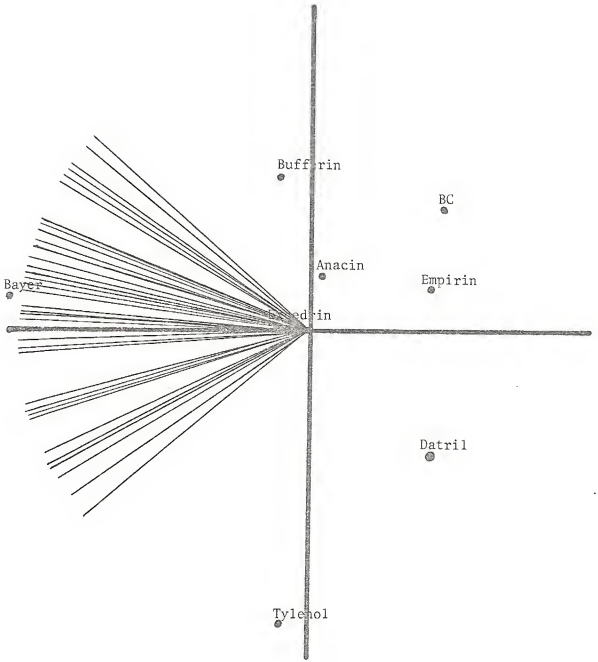

Figure 6

Product Space for Analgesic
Preference Group 2

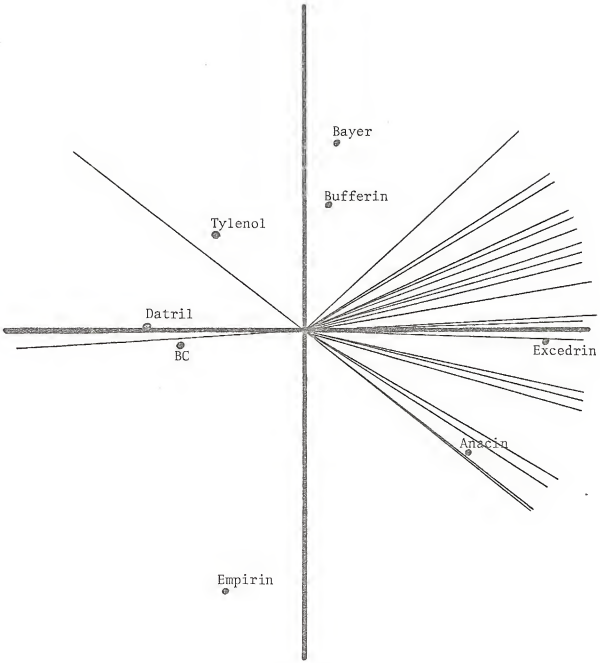

Figure 7

Product Space for Analgesic
Preference Group 3

predict that this group should purchase Excedrin and Anacin. Again, Table 7 supports this inference.

The overall strategy for penetrating this segment should be concerned with pain relieving strength and maintaining a moderate profile with respect to side effects. Table 17 shows this group to be heavy users of analgesics who spend a moderate amount of time reading newspapers. They are moderate readers of both general interest and beauty/fashion magazines. They are moderate listeners of popular programs but heavy listeners to talk shows on the radio. Lastly, they are the lightest watchers of variety programs as well as light watchers of game shows on television.

Two dimensions accounting for 79.2% of the variance (see Appendix C) describe the product space for group 4. Figure 8 represents this product space. Here, the horizontal axis seems to represent evaluation. The vertical axis is straightforward and indicates aspirin content. Use of Bufferin and, to a lesser extent, Bayer is indicated by the dimensional weights. Once again, reference to Table 7 bears this out.

This segment has maximum utility for a mild, safe analgesic that is neutral with respect to aspirin content. By referring to Table 17 this segment can be characterized as moderate users of analgesics. The time they spend reading newspapers also tends to be relatively moderate.

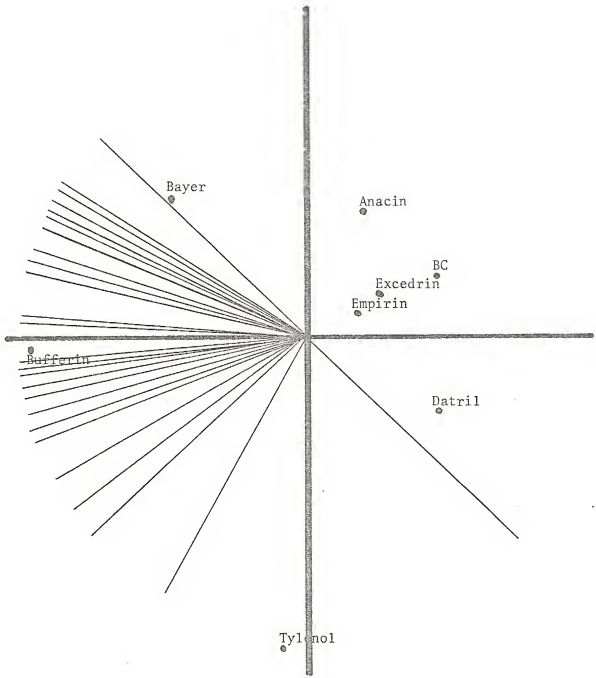

Figure 8

Product Space for Analgesic
Preference Group 4

They are heavy readers of general interest magazines, but are the lightest readers of beauty/fashion magazines. Popular radio programs are listened to rather lightly whereas talk shows are listened to moderately. Both variety programs and game shows are watched lightly on television.

The product space for group 5 consists of 3 dimensions accounting for 84.6% of the variance (see Appendix C). The first and third dimensions are depicted in Figure 9. Interpretation of the second dimension for this group is unclear in meaning, but it appears that the first, or horizontal, dimension represents generalized evaluation and the third, or vertical, dimension is aspirin content. The position of the importance weight vectors would predict that Empirin and Tylenol are the primary brands used by this group. The purchases recorded in Table 7 mainly support this prediction.

The strategy for penetrating this market calls for a moderate position with respect to aspirin content and increasing evaluation as an effective pain reliever. This segment contains the lightest users of analgesics according to Table 17. They are heavy newspaper readers. In regard to magazines, their readership of general interest types is the lightest while for beauty/fashion it is moderate. They are moderate listeners of both popular programming and talk shows on the radio. For television, they are light watchers of both variety and game shows.

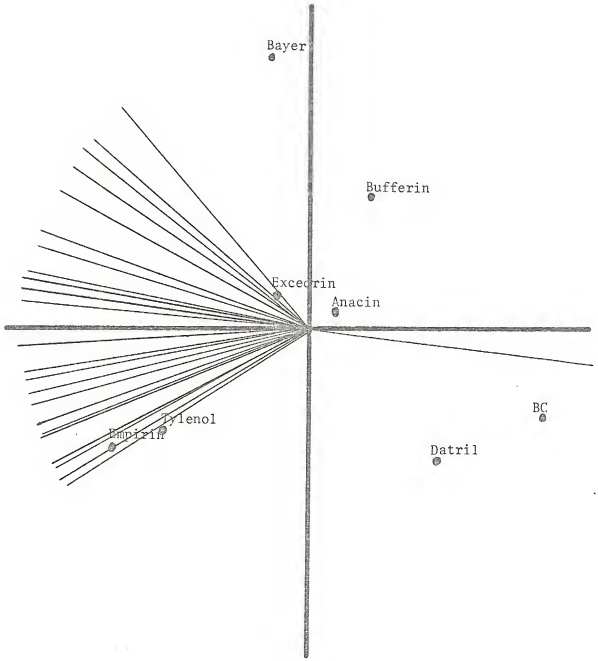

Figure 9

Product Space for Analgesic
Preference Group 5

Group 6 can be represented by 2 dimensions accounting for 69.6% of the variance (see Appendix C) which are depicted in Figure 10. The horizontal dimension seems to be concerned with evaluation while the vertical dimension is difficult to interpret. Anacin should be the most widely purchased brand in this segment followed closely by Bayer and Tylenol. The data of Table 7 shows that this is the case. The primary emphasis in concentrating on this segment should be on competing with Anacin and taking a moderate posture in regard to speed of action, length of relief, and side effect causality.

From a tactical standpoint this segment comprises the heaviest users of the product class. They also spend the most amount of time reading newspapers. They are the heaviest readers of general interest magazines whereas they are moderate readers of beauty/fashion magazines. With regard to radio they are the lightest listeners to popular programs but are tied as heaviest listeners to talk shows. They watch variety programs moderately but watch game shows more than any other group according to Table 17.

Lastly, Figure 11 depicts the product space for group 7 which can be represented by two dimensions explaining 79.8% of the variance (see Appendix C). The horizontal dimension can be interpreted as a evaluative one while the vertical dimension is difficult to interpret. The subject's importance weight vectors forecast a preponderance of Tylenol users with some Bayer and Excedrin purchasers in

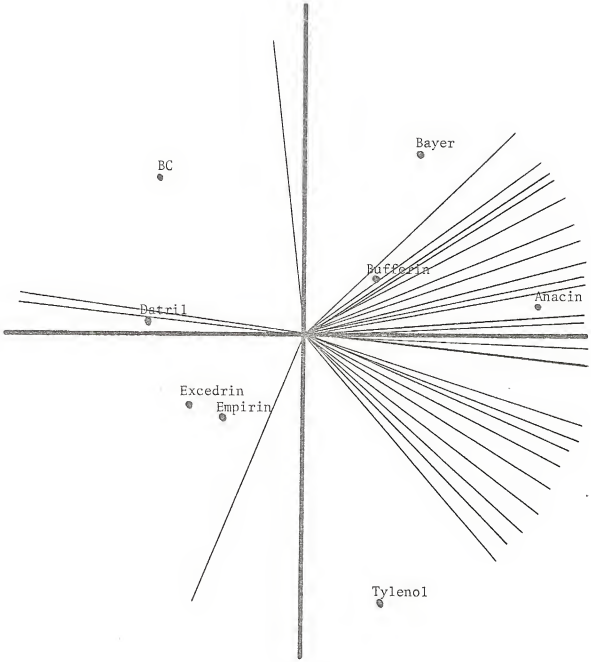

Figure 10

Product Space for Analgesic
Preference Group 6

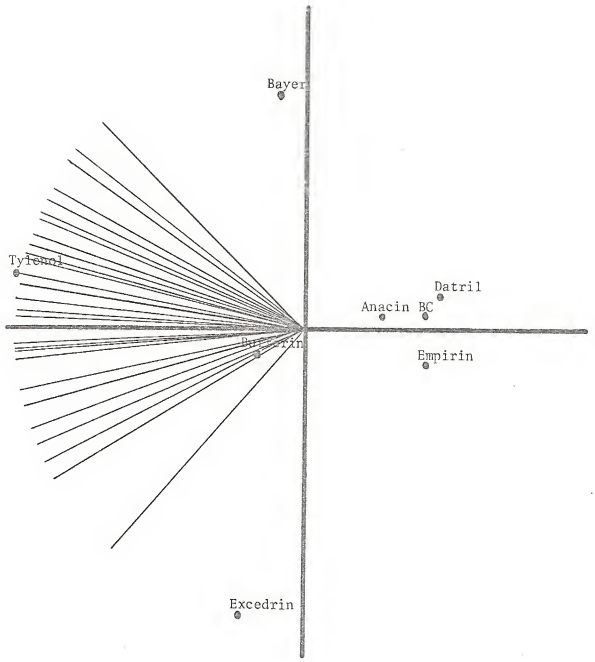

Figure 11

Product Space for Analgesic
Preference Group 7

the group. Inspection of Table 7 again points out the veridicality of this prediction.

Positioning with respect to this segment requires competing with Tylenol. Members of this group are light users of the product class as can be seen by reference to Table 17. They are heavy newspaper readers as well as heavy readers of beauty/fashion magazines. Also, they are moderate listeners to popular radio programs and tied for heaviest talk show listeners. For television they are the heaviest watchers of variety shows and heavy watchers of game shows.

Summary. The results of this study reported above can only be considered as mildly supportive of the belief that segmentation using preference data as input is more efficient and useful than using importance ratings. The use of preference data to identify segments of the analgesic market is logical, straightforward, and parsimonious and does in fact lead to market segments which are different from other more traditional methods. Unfortunately, these segments cannot be characterized very efficiently by background demographic variables.

With respect to product usage, the preference segments do exhibit much more significantly different brand purchasing than do segments based upon importance ratings. Also, the perceptual product spaces that can be developed from such preference data are more specific

to the segment and can provide beneficial inputs to the development of meaningful marketing strategy.

Unfortunately, however, unvariate analysis and multiple discriminant analysis indicate that not as many marketing mix variables are associated with the preference groups as had been believed. Still, the significant variables increased the discriminant performance by 6.7% over spurious classification for the preference groups and only 4.3% for the importance groups. When more variables are included it was shown that the preference groups increased predictability by 12.1% over spurious performance while the importance groups only increased predictability by 4.6%. Thus, it would seem that the preference groups are slightly more related to marketing variables.

Floor Cleaners

The same analyses discussed above will be undertaken again only this time for the hard-surface floor cleaner market. Thus, the interests of the study will deal with the three criteria for meaningful segmentation and the areas of inquiry outlined in Chapter III that are derived from them. The concern then is still with the issues of identification of segments, their brand usage, and their sensitivity to marketing mix variables. Before proceeding, however, a caveat is in order. Due to the high

incidence of wall to wall carpeting in the homes of Florida residents, respondent's experience with hard-surface floor cleaners is somewhat limited. For this reason there is more missing data involved here than was the case with the analgesic market.

Identification and Usage

Again, the first task to be undertaken is to determine the various segments of the floor cleaner market. Therefore, each subject's importance ratings for the 11 floor cleaner attributes outlined above were submitted to inverse factor analysis, or Q analysis, since the emphasis is on identifying consumers who have similar profiles, or utility, for the various attributes.

Two of the subjects rated all 11 of the attributes equally and had to be eliminated from the analysis since their profile is a constant with no variance. The remaining subjects were factor analyzed and inspection of their eigenvalues indicated that 7 factors should be retained which account for 89.7% of the variance (see Appendix C) in the original data. The loadings on the 7 factors were submitted to varimax rotation and each subject's loading on a factor was indexed to the average loading on that factor. Assigning respondents to the factor where they have the highest index resulted in 33 individuals being allocated to group 1, 32 to group 2, 32 to group 3, 29 to group 4, 28 to group 5, 24 to group 6, and 19 to group 7.

Analysis of the mean rating on the 11 attributes for each group presented in Table 18 indicates that they consider more attributes important when selecting floor cleaners than they did for analgesics. Ease of application, non-yellowing shine, cleaning effectiveness, fragrance, and removal of old wax are the most important attributes for group 1. In general they seem to be concerned with the products ability to get floors clean and presentable. Group 2 places above average importance on non-yellowing shine, cleaning effectiveness, long lasting shine, removal of old wax, quick drying, useful for different floor types, price, shines after mopping, and resists scuffing. In short, they seem to be interested in obtaining the best product for the money. Group 3 rates all of the attributes as highly important with the exception of price. They seem to be interested in obtaining the best possible product regardless of cost. The value and efficiency of the product seem to be the overriding concerns of group 4. Their ratings indicate high importance for ease of application, non-yellowing shine, removal of old wax, quick drying, and price. The most important attributes for group 5 include non-yellowing shine, long lasting shine, shines after mopping, and resist scuffing. This group seems to be interested in finding a product that needs to be used only infrequently. On the other hand, group 6 seems to be more concerned with the aesthetics of the product. They rate fragrance, removal of old wax,

Table 18

Mean Attribute Rating for Floor Cleaner Importance Groups

Attribute	Group 1	2	3	4	5	6	7
Application ease	5.97	5.44	6.09	6.14	5.18	4.67	6.00
Non-yellow shine	6.36	6.16	6.37	6.52	6.50	5.67	3.32
Effectiveness	6.52	6.53	6.47	6.24	5.82	6.17	5.79
Fragrance	3.06	1.78	3.78	2.97	2.82	3.29	2.74
Long lasting	5.12	6.19	5.94	5.79	5.93	5.33	5.53
Removes wax	5.58	5.56	6.34	6.21	3.04	5.50	4.63
Quick drying	2.39	5.09	5.09	5.34	3.71	4.87	4.63
Many floors	2.79	5.84	4.22	2.14	2.93	4.54	4.00
Price	4.45	5.28	2.97	4.93	4.43	4.62	4.47
Shines after mopping	5.27	6.12	6.25	5.21	6.07	5.33	4.79
Resist scuffing	4.79	6.22	6.09	5.83	6.18	5.67	4.32

useful for different floor types, and price as more important. Finally, group 7 places above average importance on ease of application, quick drying, and useful for different floor types. They seem to be primarily interested in eliminating effort.

The assumption underlying benefit segmentation that consumers desiring similar attribute bundles will purchase the same brand can be checked by reference to Table 19. The crosstabulation denotes that the groups do not purchase significantly different brands.

Inspection of this table shows that there are a number of cells with very low expected frequencies and, thus, a chi-square statistic may be inappropriate. In order to correct this a number of rows were combined. Specifically, the Aero Wax, Floor Shine, Glo Coat, and Step Saver rows were combined as well as the Future and Klear rows. Also, the missing row was added to the other row. Now, there are 7 groups times only 4 rows: Mop & Glo, the wax brands, the acrylic brands, and other brands. Crosstabulation now produces a significant chi-square which rejects the hypothesis of independence between the groups and the brands.

The paired comparison preferences were submitted to the orthogonal analysis of variance in order to test the significance of the respondent's scale values. Table 20 presents the results for the overall analysis of variance which shows that the scale values are highly significant while the unscalability is not. Further support is provided

Table 19

Crosstabulation of Floor Cleaner
Importance Groups with Brand Purchased

	Group						
Brand	1	2	3	4	5	6	7
Aero Wax	3	2	4	1	0	1	2
Floor Shine	1	0	0	0	0	0	1
Future	0	5	2	3	3	4	1
Glo Coat	1	0	0	2	0	3	0
Klear	0	3	0	2	6	3	0
Mop & Glo	11	10	12	5	7	3	4
Step Saver	4	4	5	3	2	1	5
Other	12	7	9	12	8	8	6
Missing	1	1	0	1	2	1	0

Chi-Square = 31.954*

DF = 18*

Probability = 0.0223*

Cramer's V = 0.233

* based upon a contingency table having combined rows (see text)

Table 20

ANOVA for Floor Cleaner Preferences

Source	SS	DF	MS	F
Scales	30545.714	1194	25.583	8.221*
Unscalability	70.317	15	4.688	1.506
Error	9241.968	2970	3.112	
Total	39858.000	4179		

*probability > .001

by the fact that the validity correlation coefficient between the original preferences and the scale values equals .867 whereas the reliability correlation coefficient between the preferences and the scale values plus the unscalability is .870. Thus, the individual preferences can be predicted from the scale values with a good deal of accuracy. Unfortunately, partitioning of the sum of squares of the scale values into orthogonal components for each subject results in 27 subjects who have non significant F values and their mean validity coefficient is only .619. Most probably this is due to the number of respondents who have no need of this product as pointed out above and thus, they are indifferent among the brands. While 27 individuals may at first glance seem like a lot to delete, it must be remembered that the purpose of this study is to find meaningful segments. If some individuals are not prospects for the product they should be considered outlyers and not forced into some segmentation procedure.

The remaining 172 respondents were submitted to the factor analytic procedure outlined above. Here, there are 7 brands and so the intercorrelation matrix derived from the subject's profiles has only 6 non zero eigenvalues (see Appendix C). By retaining all 6 factors, 100% of the variance in the scale values can be explained. This is appropriate since it provides for a relatively small number of groups roughly equal to the number of importance groups, and the loyal customers of a brand should comprise a separate segment.

The indexing procedure places 41 individuals in group 1, 29 in group 2, 26 in group 3, 30 in group 4, 22 in group 5, and 24 in group 6. The average scale values for each group is shown in Table 21.

The crosstabulation presented in Table 22 shows that the brand purchases of these groups are very significantly different. Again, a number of cells have very low expected frequencies and the chi-square statistic may be inappropriate. In order to correct this a number of rows were combined. Specifically, the Aero Wax, Floor Shine, Glo Coat, and Step Saver rows were combined as well as the Future and Klear rows. The missing row was added to the other row also. Now there are 6 groups times only 4 rows: Mop & Glo, the wax brands, the acrylic brands, and other brands. Crosstabulation of these brands produces a highly significant chi-square indicating that while both the importance groups and the preference groups exhibit differential behavior with respect to brand purchasing, the preference groups are more strongly associated with brand purchasing as evidenced by Cramer's V statistics.

Marketing Mix Elements

The crosstabulation shown in Table 23 signifies that while the two grouping methods are not independent the relationship between them is very low as evidenced by the Cramer's V statistic. Therefore, it is appropriate to

Table 21

Mean Scale Values for
Floor Cleaner Preference Groups

Brand	Group 1	2	3	4	5	6
Aero Wax	-1.98	0.24	-0.41	-0.17	1.28	-0.11
Floor Shine	-1.51	-1.15	-0.94	-1.39	-1.28	-0.58
Future	-0.12	0.48	-0.46	2.42	-1.19	-0.59
Glo Coat	-1.22	-0.01	-0.57	-0.98	-0.27	1.08
Klear	-0.23	0.60	-0.24	0.05	2.16	-0.52
Mop & Glo	2.26	0.20	2.81	0.32	-0.27	1.03
Step Saver	2.80	-0.35	-0.19	-0.26	-0.44	-0.31

Table 22

Crosstabulation of Floor Cleaner Preference Groups with Brand Purchased

	Group					
Brand	1	2	3	4	5	6
Aero Wax	0	4	0	2	5	2
Floor Shine	1	0	0	0	1	2
Future	0	4	1	12	0	0
Glo Coat	0	1	0	0	1	3
Klear	1	5	1	1	5	0
Mop & Glo	15	4	17	4	3	5
Step Saver	15	2	1	2	1	2
Other	8	9	4	8	6	9
Missing	1	0	2	1	0	1

Chi-Square = 60.405*

DF = 15*

Probability = 0.0001*

Cramer's V = 0.342

* based upon a contingency table having combined rows (see text)

Table 23

Crosstabulation of Floor Cleaner Importance Groups with Preference Groups

Preference Group	Importance Group						
	1	2	3	4	5	6	7
1	9	2	11	8	3	3	4
2	2	4	3	9	6	3	2
3	9	6	4	1	4	0	2
4	0	8	5	1	5	6	5
5	5	2	5	2	4	3	1
6	3	4	3	2	5	5	1

Cramer's V = 0.243

compare them since their performance with respect to the other criteria will not be the same.

The same 33 variables dealing with price, distribution and promotion are available for use in discriminating amongst the group members. Again, the type of store where subjects usually purchase floor cleaners and the place they usually listen to the radio were deleted since so many respondents failed to answer those questions.

Importance groups. The importance groups were tested using crosstabulation and analysis of variance for differences in group means on the 33 variables. The significance levels for the resulting univariate statistics are presented in Table 24. At an alpha level of .10 only two variables were significantly different among the groups:

- time reading newspapers
- watching television talk shows

In order to make use of the covariance structure in characterizing the groups multiple discriminant analysis was employed. As will be discussed later, the floor cleaner data contained fewer violations of the assumptions of linear discriminant analysis. Thus, the results of this section are perhaps more indicative of the relationship between groups membership and marketing mix elements.

Table 24

Significance of the Floor Cleaner Importance Group Means on the Marketing Variables

Variable	Probability Level
Percent of time brand used	.8828
Amount used	.2080
Buy at same store	.3679
Price increase for switching	.1219
Check ads for sales	.3736
Clip and use coupons	.1934
Number of newspapers read	.8609
Time reading newspapers	.0264**
Magazine type readership	
Beauty/Fashion	.1114
News	.4075
Sports	.5208
Home/Garden	.1843
Movie	.6734
Hobby	.3617
General Interest	.4644
Time reading magazines	.6018
Radio program listening	
Popular	.2205
Easy listening	.4855
Classical	.7499

Table 24 - continued

Variable	Probability Level
News/Weather	.4058
Talk show	.2024
Time listening to radio	.7182
Radio frequency	.2816
Television program watching	
News/Weather	.6411
Sporting events	.9065
Movies	.9430
Action	.9601
Comedy	.3833
Variety	.8498
Game shows	.1753
Talk shows	.0532*
Time watching television	.9714
Consultation with others	.2130

* $p>.10$

** $p>.05$

The variables were submitted to the SPSS stepwise discriminant procedure to determine which variables contribute most to discrimination among the groups. Using a change in Rao's V greater than the .10 alpha level for inclusion into the model, the following 4 variables were found to contribute significantly:

- time reading newspapers
- watching television talk shows
- reading beauty/fashion magazines
- reading home/garden magazines

The first two of these variables are the same as found in the univariate results. These variables were then used to discriminate the importance group membership. Since there are missing observations, the sample size fell to 194 from the original 197. Of these, the model correctly classified 56 of the observations as shown in Table 25, a score of 28.9%.

In order to determine a base line for spurious results three randomized discriminant runs were performed. These classified 23.2%, 25.3%, and 26.8% correct respectively. Thus, on an average the importance groups increased predictability by 3.7% over randomized segments.

Preference groups. The same process was undertaken to discriminate among the preference groups. Crosstabulation and analysis of variance produced 4 variables that have significantly different group

Table 25

Classification Matrix for Floor Cleaner Importance Groups Using Marketing Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	12	2	5	6	7	0	1
2	4	7	8	3	7	0	2
3	5	3	12	4	7	0	1
4	7	4	4	7	5	0	1
5	3	3	5	1	14	0	1
6	5	3	11	2	3	0	0
7	5	0	3	2	5	0	4

Total number = 194

Number correct = 56

Percent correct = 28.9%

means for the preference groups at an alpha level of .10 as seen in Table 26. These variables are:

- reading beauty/fashion magazines
- listening to popular radio programs
- watching television sporting events
- watching television comedy shows

In order to ascertain the effect of the covariance structure, multiple discriminant analysis was employed. Again, not all of the assumptions of the discriminant model were violated and implications drawn from the results should be indicative of a true relationship. The stepwise procedure using the same Rao V criterion was used and the following 5 variables were found to make significant contributions:

- watching television sporting events
- listening to popular radio programs
- watching television news/weather
- listening to news/weather on radio
- amount used

This time only the first two variables are the same as found in the univariate results. These variables were used to discriminate the preference groups. A number of observations contained missing data and the sample size falls to 165 from the original 172. As can be seen in Table 27, this model classified 50 of the observations correctly, a score of 30.3%.

Three discriminant runs randomizing group membership were undertaken and they produced 26.1%, 31.5%,, and 31.5% correct classifications respectively. Thus, placing the

Table 26

Significance of the Floor Cleaner Preference Group Means on the Marketing Variables

Variables	Probability Level
Percent of time brand used	.6886
Amount used	.1162
Buy at the same store	.8415
Price increase for switching	.9292
Check ads for sales	.8625
Clip and use coupons	.8399
Number of newspapers read	.6904
Time reading newspapers	.9171
Magazine type readership	
Beauty/Fashion	.0555*
News	.5095
Sports	.4469
Home/Garden	.7993
Movie	.6790
Hobby	.8181
General Interest	.1757
Time reading magazines	.8305
Radio program listening	
Popular	.0141**
Easy listening	.3064
Classical	.1910

Table 26 - continued

Variable	Probability Level
News/Weather	.1107
Talk show	.9820
Time listening to radio	.5319
Radio frequency	.9142
Television program watching	
News/Weather	.1966
Sporting events	.0118
Movies	.8849
Action	.2575
Comedy	.0857*
Variety	.6218
Game shows	.9957
Talk shows	.9259
Time watching television	.4938
Consulting with others	.6728

* p>.10

** p>.05

Table 27

Classification Matrix for Floor Cleaner Preference Groups Using Marketing Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	25	1	0	7	3	3
2	10	9	0	4	4	2
3	13	4	0	7	0	0
4	10	6	0	8	2	4
5	4	5	0	8	3	2
6	6	3	0	5	2	5

Total number = 165

Number correct = 50

Percent correct = 30.3%

observations in the groups increases predictability by only 0.6%.

It was desired to see if the addition of more variables would increase the performance of the discriminant function since the significant ones are such a small subset. The stepwise procedure was employed using the partial F of 1.0 as the criterion for inclusion. It resulted that 16 variables contributed to the importance group classifications while 15 contributed to the preference group classifications.

For the importance groups the 16 variables classified 43.6% correctly. Three randomized runs produced correct classifications of 39.1%, 40.4%, and 41.7%. Thus, on the average the real importance groups increased predictability by 3.2%.

The 15 variables classified 45.7% of the preference groups correctly. The randomized procedure resulted in 35.7%, 40.1%, and 41.4% correct classifications, an increase of 6.6% on the average.

Demographics. Next, it is of interest to determine if these groups can be characterized using the respondent's demographic variables. First, the 4 nominal variables, marital status, race, religion, and occupation of the household head, were crosstabulated with the importance groups to ascertain if there were any differences among the groups on these variables. For these variables the resulting chi-square values were 37.842, 15.366, 25.468, and 35.573

respectively. At the associated degrees of freedom only marital status was significant at the .05 alpha level. Accordingly, it was recoded into a binary zero/one depending on whether or not the subject was currently married. The other 3 variables were dropped from the analysis.

The results of using the demographic variables to discriminate the importance groups appear in Table 28. Sixty-three of the 182 observations are classified correctly, a score of 34.6%. It should be kept in mind that while all of the variables were used; only 3, income, age, and number of children, were significant at the .10 alpha level according to the change in Rao's V criterion.

A crosstabulation was run to determine if there are any differences among the preference groups on marital status, race, religion, and occupation of the household head. The respective chi-square values were 33.904, 6.279, 23.194, and 51.544. At the relevant degrees of freedom, both marital status and occupation of the household head were significant at the .05 alpha level. Therefore, these were recoded into binary zero/one variables, marital status into married/not married and occupation into salaried/non salaried.

These 2 variables were then combined with the other 7 demographic variables and used to discriminate the preference groups. The results appear in Table 29 and show that 54 of the 155 subjects were classified correctly, a score of 34.8%.

Table 28

Classification Matrix for Floor Cleaner Importance Groups Using Demographic Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	17	4	4	1	2	1	2
2	2	12	5	2	2	2	3
3	7	3	13	0	2	3	1
4	5	6	7	1	3	3	1
5	2	3	5	1	9	2	3
6	4	2	2	1	5	8	2
7	8	1	2	0	2	3	3

Total number = 182

Number correct = 63

Percent correct = 34.6%

Table 29

Classification Matrix for Floor Cleaner Preference Groups Using Demographic Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	25	8	0	5	0	1
2	8	6	0	6	2	4
3	11	2	1	4	4	2
4	10	4	3	8	2	2
5	4	3	2	2	7	1
6	2	3	3	1	2	7

Total number = 155

Number correct = 54

Percent correct = 34.8%

Again, while all of the variables were used, only 3, age, income, and number of children, were significant at the .10 alpha level according to the change in Rao's V criterion. Thus, demography does not seem to provide as much predicability as the other two data inputs and really does not do much better than what might be expected due to spurious association.

Interpretation of the above results should be undertaken with care since obviously the variables used have violated the assumption of multivariate normality. However, for the floor cleaners the quality of the covariance matrices was tested and could not be rejected. Thus, the discriminant functions are less likely to be inappropriate.

Marketing Implications

The eigenvalues associated with the subject's scale values are presented in Table 30 and plotted in Figure 12. There are 6 non zero eigenvalues since the floor cleaner scale values sum to zero. Inspection suggests retaining 3 dimensions.

This conclusion is affirmed by reference to Table 20 in conjunction with Table 30. It can be determined that the sum of squares of the scale values associated with the unused eigenvalues come to 28.2% of the variance, a value of 8613.8913. Comparing this with the error sum of squares signifies that fitting a three dimensional submodel to the data does not increase error that much.

Table 30

Eigenvalues Obtained from Floor Cleaner Scale Values

Number	Value	Percent	Cumulative
1	1529.712	.357	.357
2	947.150	.221	.578
3	602.270	.140	.718
4	498.892	.116	.834
5	427.314	.100	.934
6	281.762	.066	1.000
7	0.000	.000	1.000

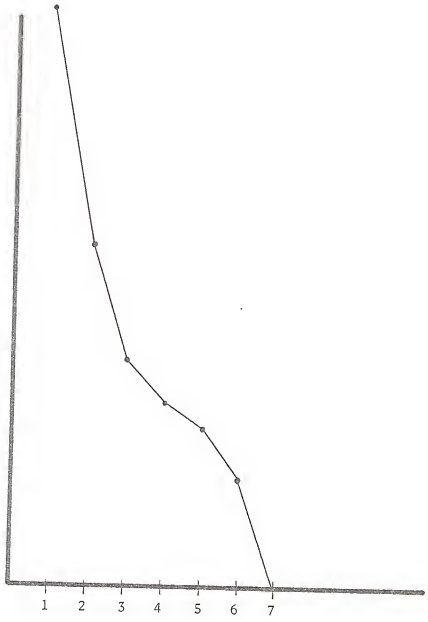

Figure 12

Eigenvalues Derived from
Floor Cleaner Scale Values

Figure 13

Product Space for Floor Cleaner
Preference Group 1

The coordinates of the floor cleaner brands appear in Table 31. Since most subjects have a negative weight for the first dimension and there is a preponderance of Mop & Glo users in the sample (see Table 22), it appears that this dimension represents an evaluation of the products ability to get floors clean and shiny. Order of the brands on the second dimension seems to be concerned with whether the brand is a wax or an acrylic. The third dimension is much more difficult to interpret and probably represents some subjective attribute of the product class.

As explained in the analgesic section it may be more meaningful to develop product spaces for respondents with similar scale values. Therefore, each preference group identified above was submitted to a separate vector sub-model analysis. Inspection of the eigenvalues obtained from the scale values of group 1 indicates that 78.8% of the variance (see Appendix C) can be explained by one dimension. This uni-dimensional product space for group 1 appears in Figure 13. All of the individuals in this group have negative weight for this dimension and, thus, it would be expected that this group is comprised mainly of Step Saver users followed closely by Mop & Glo users. The data in Table 22 shows that this is indeed the case.

Penetration of this market segment would be dependent upon a strategy of competition with Step Saver. Reference to Table 32 shows that this group tends to be light users of floor cleaners. They read beauty/fashion magazines the

Table 31

Coordinates of the Floor Cleaner Brands
in the Common Product Space

Brand	Dimension 1	2	3
Aero Wax	0.381	-0.461	0.399
Floor Shine	0.298	-0.176	-0.689
Future	0.047	0.721	0.038
Glo Coat	0.264	-0.173	0.032
Klear	0.153	0.367	0.326
Mop & Glo	-0.666	-0.270	0.302
Step Saver	-0.477	-0.007	-0.408

Table 32

Floor Cleaner Preference Group Means
for Significant Marketing Variables

Variables	Group 1	2	3	4	5	6
Amount used	103	170	102	105	217	162
Beauty/Fashion magazine	0.51	0.34	0.50	0.47	0.18	0.25
Popular radio	0.67	0.34	0.54	0.37	0.27	0.24
News/Weather radio	0.36	0.55	0.46	0.57	0.68	0.43
News/Weather television	0.85	0.59	0.71	0.70	0.77	0.62
Sports television	0.41	0.34	0.25	0.13	0.14	0.14
Comedy television	0.32	0.34	0.31	0.27	0.41	0.29

most. Also, they listen most to popular programs but least to news/weather on the radio. For television, they are the heaviest watchers of news/weather and sports but moderate watchers of comedy.

The 2 dimensions used by group 2 are shown in Figure 14 and account for 74.3% of the variance (see Appendix C). The horizontal dimension probably is concerned with the wax/acrylic continuum while the vertical dimension is rather difficult to interpret. The weight vectors are very difused in this space and imply that the most used brands should be Future, Klear, Mop & Glo, and Aero Wax. Table 22 supports this contention.

There are a number of possible strategies that can be used with regard to this group. It would seem that any strategy used should take a definite position as either a wax or an acrylic. Group members tend to be moderate users of the product class. They are moderate readers of beauty/fashion magazines, moderate listeners of popular radio programs, and heavy listeners of news/weather radio programs. Conversely, they are the lightest watchers of television news/weather, heavy watchers of sports, and moderate watchers of comedy as shown in Table 32.

Figure 15 depicts the product space for group 3 which is uni-dimensional in nature and accounts for 80% of the variance (see Appendix C). Fully 24 of the 26 group members have a negative weight for this dimension and thus the

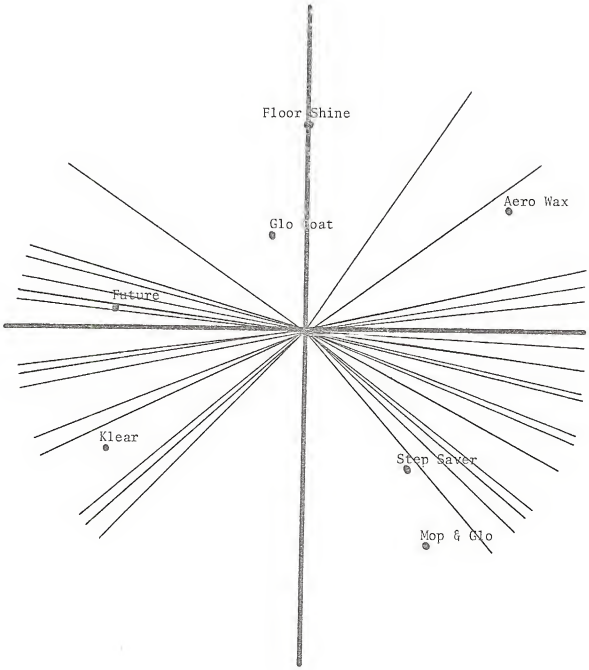

Figure 14

Product Space for Floor Cleaner
Preference Group 2

Figure 15

Product Space for Floor Cleaner
Preference Group 3

expectation is for a large majority of Mop & Glo users. The data in Table 22 bear this out.

Strategically, appeals to this group should focus on attacking the Mop & Glo position. The group members are light users of the product class. They are heavy readers of beauty/fashion magazines and heavy listeners to popular radio programming according to Table 32. For news/weather, sports, and comedy they are relatively moderate.

Two dimensions explaining 77% of the variance (see Appendix C) correspond to the perceptual structure of group 4 as shown in Figure 16. The horizontal dimension seems to represent the wax/acrylic continuum while the vertical dimension is more difficult to interpret. From the importance vectors one would expect the segment to be dominated by Future users and Table 22 supports this notion.

From a strategic standpoint, appeals aimed at this segment should stress the acrylic nature of the product. This segment tends to be light product class users according to Table 32. They are heavy magazine readers for the beauty/fashion category. Also, they are moderate listeners to popular programs but heavy listeners of news/weather on the radio. While they watch television news/weather moderately, they are the lightest watchers of sports and comedy.

The product space for group 5 has 2 dimensions and accounts for 74.6% of the variance (see Appendix C), and is depicted in Figure 17. The dimensions are difficult to

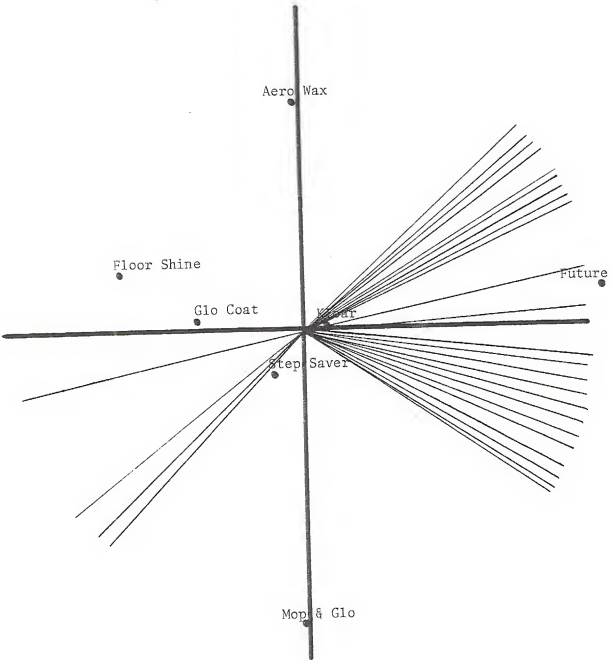

Figure 16

Product Space for Floor Cleaner
Preference Group 4

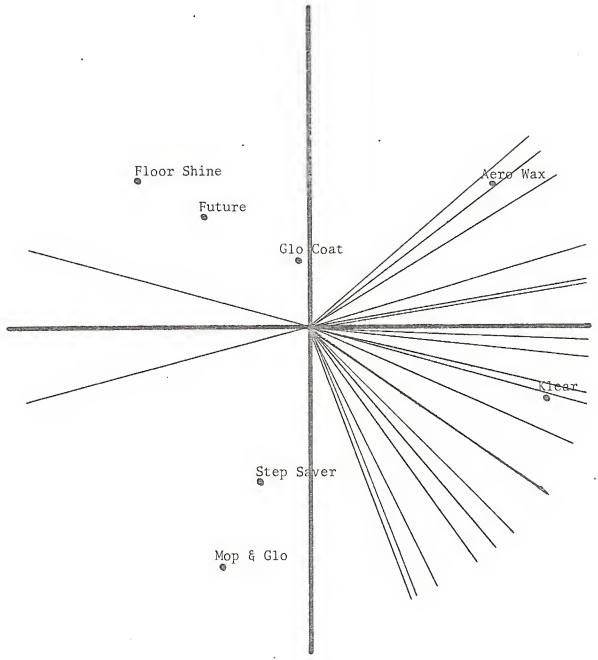

Figure 17

Product Space for Floor Cleaner
Preference Group 5

label without ancillary information, but the segment members seem to have the most utility for the horizontal dimension and it would be expected that Aero Wax, Klear, and Mop & Glo should all be well represented. In fact, this seems to be the case as Table 22 attests.

Appeals aimed at this segment should stress comparisons with Glo Coat. Table 32 shows that this segment comprises the heaviest users of floor cleaners and the lightest readers of beauty/fashion magazines. On the radio they are light listeners of popular programs but the heaviest listeners of news/weather. For television, they are moderate watchers of news/weather, light watchers of sports, but the heaviest watchers of comedy.

Figure 18 is the product space for group 6 which can be represented by 2 dimensions which explain 70.7% of the variance (see Appendix C). Again, the dimensions are difficult to interpret but it would seem that the horizontal dimension has to do with evaluation. The importance vectors imply that the segment prefers Glo Coat and Mop & Glo. It can be seen that they in fact do by referring to Table 22.

In their use of the product class, this group tends to be moderate as Table 32 attests. They are relatively moderate readers of beauty/fashion magazines. For radio, they listen to popular programs the least but news/weather moderately. Lastly, they watch television news/weather

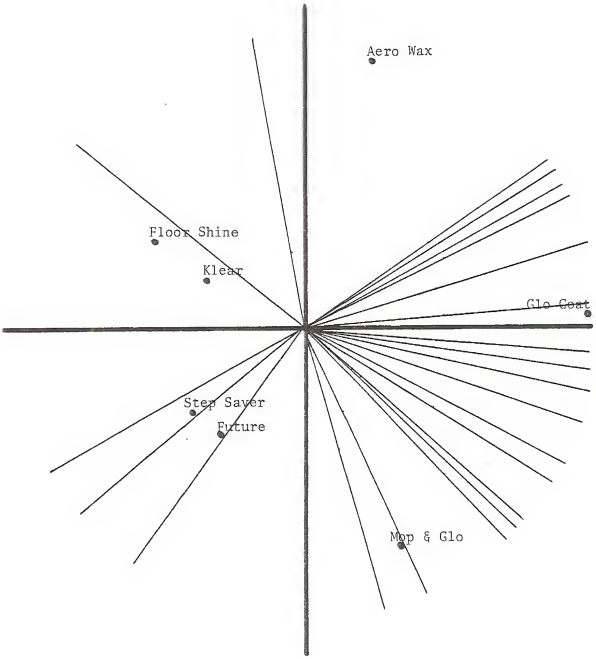

Figure 18

Product Space for Floor Cleaner
Preference Group 6

moderately and watch both television sports and comedy lightly.

Summary. The study results in the hard-surface floor cleaner market are only very weakly supportive of the superiority of the preference data as the segmentation base. This may in part be due to the sample unfamiliarity with the product class discussed above.

The use of preference data does provide segments which are more strongly associated with brand purchasing than does the use of importance ratings, although they are also significantly related. The perceptual product spaces derived from the preference data are an aid for strategy development, but are apparently less useful than had been expected.

Perhaps, the most disappointment results from the fact that the preference segments do not seem to be more associated with marketing mix variables than are the importance segments. Lastly, characterization of the segments by means of background demographic variables can not be accomplished to any extent for either measurement method.

CHAPTER V
SUMMARY AND CONCLUSIONS

The focus of this study has been on the issue of market segmentation. During the past few decades segmentation has been a topic of considerable interest in the marketing literature. Yet, for all of the research that has been undertaken, the principles for effectively segmenting markets are not well understood. This fact has been dramatically stated by Wilkie (1970, p. 10) who points out that "In over ten years of study leading academicians have consistently and spectacularly failed to discover meaningful segments."

More recently, proponents of the product stream approach (Haley, 1968; Yankelovich, 1964) have indicated that measures dealing with the interface between the consumer and the product are more meaningful than measures dealing with only inherent characteristics of the consumer. They argue that this is true with respect to brand purchasing. Still, no specific methodology has been divulged by these practitioners and researchers employing this approach have been forced to use their own procedures. The result of this has been an inability to substantiate the claims that have been made for this approach.

It is from within the product stream orientation that this study has been undertaken. A simplified view of consumer behavior from a segmentation perspective was presented in Chapter I. It was posited that measures which are closely related to overt behavior should be more useful for segmenting markets than measures of more latent constructs such as desired product benefits. These behavioral antecedent measures are consumer's brand preferences.

The purpose of the study then, was twofold. The first was to specify a specific procedure for isolating market segments given some measure as input. The second was to use brand preferences as the input and to compare segments so derived with segments developed from the measures usually employed by researchers (Wilkie, 1970; Mitchell, 1974) in the product stream. These measures have consisted of subject's importance ratings for various attributes of the product class.

The comparison of the two segmentation bases was the degree to which they fulfilled the criteria for meaningful segmentation outlined in Chapter I. Specifically, the study focused upon the identification of segment membership, their reported brand purchasing, and their differential responsiveness to various elements of the marketing mix.

Findings

The first thing that should be noted is that it would seem that the analgesic market seems to be much more stable than the floor cleaner market. Inspection of Table 3 and Table 18 indicates that the importance ratings for the analgesic attributes exhibit higher variances than do the importance ratings for the floor cleaner attributes. This may be taken as an indication that the benefits desired from analgesics are more well defined than are the benefits desired from floor cleaners where all of the attributes tend to be rated equally.

This stability is also found for the brand preferences. As shown in Table 5 and Table 20, the sum of squares associated with the scale values is a larger percentage of the total sum of squares for analgesics. Also, a greater number of individuals have scales which indicate indifference among the brands of floor cleaners than among the brands of analgesics.

As stated in Chapter IV, this instability in the floor cleaner market may result from characteristics of the area where the sample was obtained. Since there is less need for this product it would be expected that consumers be somewhat indifferent towards the product class. However, the explanation for their indifference may be that they have low involvement with floor cleaners. That is, they may not have definite preferences with respect to floor cleaner

brands or attributes because quite simply they do not care as much about having clean floors as they do about relieving pain.

With regard to the identification of segment membership, both procedures began by defining groups on the basis of their similarity with respect to the measures used. That is, segments were isolated so as to be homogeneous with respect to their importance rating profile on the one hand, and their brand preference scales on the other. Attempts to characterize group membership by means of background demographic variables were largely unsuccessful and indicate that these variables are not useful to the product stream approach.

As far as brand purchasing of analgesics, the use of preference measures results in segments which exhibit significantly different purchasing proclivities. The importance ratings, on the other hand, result in segments which are independent of brand purchasing. These results are similar to those found by Wilkie (1970) and De Bruicker (1973), which were reported in Chapter II. In the floor cleaner area both measures produce segments which have significantly different brand purchasing, although the relationship is stronger for the preference groups.

Attempts to relate the segments to marketing mix variables were largely disappointing, although the results were more encouraging for analgesics than for floor cleaners. The use of variables that were significant

beyond the .10 alpha level in a discriminant analysis showed that the preference groups performed only slightly better than did the importance groups. When more variables were added to the discriminant function performance of the preference groups was a good deal better than the importance groups. The same type of analysis of floor cleaners resulted in slightly better performance by the importance groups when the discriminant function included only those variables significant at the .10 alpha level. The addition of more variables resulted in somewhat superior performance by the preference groups.

Since the concern is with trying to find marketing mix elements which are related to market segmentation, it should be noted that a few variables were found to be significant across product categories. Both the amount of the product used and popular radio program listening were significantly different among the preference groups for both analgesics and floor cleaners. Watching talk show television programs was significantly different among the importance groups for both product categories. It could possibly be that popular radio broadcasts and television talk shows are instrumental in providing information upon which brand preferences and attributes desired are based. Also, there exists a relationship between the amount used and brand preference reaffirming that usage is a classic and useful variable for segmenting markets.

The advantage preference measures have in serving as input for multidimensional scaling is less useful for strategy development than had been hoped. Many of the dimensions uncovered for various preference groups were difficult to interpret and did not provide specific guidelines for brand positioning. The validity of the group spaces was verified by the close correspondence between the individual vectors and brand purchases.

Considering the results in toto, while the superiority of preference measures has not been established, there are some indications that it still may be useful for segmentation. Clearly, there are advantages in using a variable which is more strongly associated with brand choice and contains more information for developing product spaces and inferring product class attributes. The major shortcoming at this time is that preference does not seem to result from differential marketing mix responsiveness.

Limitations

The greatest limitation of the present study is the fact that the sample used in this analysis was not a random sample of the nation's consumers and is inadequate for generalizing the size, purchasing power, or competitive posture of any segment uncovered. While this is unfortunate, it was also unavoidable, and it is believed that the results

found do indicate that preference measures do have some usefulness for market segmentation.

Also, while the marketing mix variables were patterned after the price, promotion, and distribution elements, in point of fact most of the variables were concerned with promotional issues. What is needed for segmentation research are more variables dealing with the other mix elements, especially product. Consideration also needs to be given to the validity of the measures used to describe behavior. Self report techniques may not be the most effacacious way to accomplish this.

There is also the problem of interpretability of the dimensions comprising the product spaces for the segments. It is difficult to define the construct underlying the dimensions in a number of cases. This problem can probably be corrected by collection of ancillary information by several methods comprising a pattern of evidence for validating particular dimensions.

With respect to the product spaces, measures of this type are only able to uncover aspects of the product class as it currently exists. That is, only dimensions which are used by individuals to discriminate the brands comprising the product class are part of the solution. Therefore, the usefulness of the spaces is limited to repositioning of brands vis-a-vis the present dimensions. Insights into attributes which are desired by consumers

but not available from any of the brands currently being offered cannot be obtained from this process.

Future Research

The present study has not so much answered questions definitively as raised some issues requiring further study. First and foremost, of course, is the need for more representative samples which will enable researchers to address all of the issues required for meaningful market targeting. Only in this way can research provide marketing management with complete directions for strategy development.

More effort needs to be given towards developing better measures of responsiveness to marketing mix elements. Particular attention needs to be given to the validity of these measures for reporting overt behavior. More attention also needs to be given to validating the dimensions uncovered by multidimensional scaling techniques.

Results of this study indicate that the relationship between the amount of the product used and other variables bears scrutiny. Twedt (1964) has already indicated that association exists between product class usage and media habits. This study confirmed that there is a relationship between usage and brand preference, and needs to be investigated more fully.

Also, the focus of this investigation has been on the association between preference and marketing elements. If a more complete implementation of targeting strategy is ever to be achieved, more attention must be given to the causal links underlying the process. That is, a better understanding of how consumer's perceptions of marketing information is transformed into brand preference, and how preference is transformed in behavior is needed.

In this way, a better appreciation of the realities existing in the marketplace can be obtained. Given such an appreciation, marketing administration will be in a better position to provide consumers with products that fulfill their needs more efficiently. Such efficiency will obviously result in increased profitable returns to the firm.

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APPENDIX A

PHASE ONE QUESTIONNAIRE

Product Attribute Questionnaire

P. J. O'Connor
University of Florida

Before you fill out this questionnaire we would like to assure you of two things. First, your participation is completely anonymous, so please do not put your name anywhere on this form. Second, there are no right or wrong answers; we are interested only in your opinions.

Now then, there are a number of different characteristics, attributes, or qualities of products which people take into consideration when they make a purchase. For example, when buying a brand of toothpaste, some of the things a person may consider might include the following:

- Does it prevent cavities?
- Does it freshen my breath?
- Does it whiten my teeth?
- Is it a good buy for the money?
- Does it taste good?
- Does my family like it?
- What does my dentist think of it?
- Is it good for my gums?
- Does it eliminate the need for dental floss?
- Does it kill smoking odors and stains?

Of course, you may not think about these particular characteristics of toothpaste, but it represents the type of things a person may consider. On the next two pages we are interested in your opinion of the characteristics of two specific products. Please don't worry about grammar, but merely list as many characteristics as you would normally consider.

Would you please list the things you consider when buying pain relievers, such as: Anacin, Bayer, B.C., Bufferin, Datril, Empirin, Excedrin, or Tylenol.

Would you please list the things you consider when buying hard-surface floor cleaners, such as: Aero Wax, Floor Shine, Future, Glo Coat, Klear, Mop & Glo, or Step Saver.

Thank you very much for your cooperation.

APPENDIX B

PHASE TWO QUESTIONNAIRE

Survey of Purchase Behavior and Attitudes Toward Analgesics and Hard-Surface Floor Cleaners

P. J. O'Connor
Marketing Department
University of Florida

Before you complete this questionnaire we would like to assure you of two things. First, your participation is completely anonymous, so please do not put your name on this form. Second, there are no right or wrong answers; we are interested only in your opinions.

Some of the questions asked may concern products about which you may know very little. Even though your knowledge of them is not great, please answer all of the questions, even if you have to rely only on your general feelings or intuitions. Such answers are acceptable and are encouraged. Your every answer is vital to the success of this project, so mark every answer based on the best information you personally have or on your general impressions.

Now then, on the following four pages there are some choice questions which ask you to tell us how much more you like one brand than another. For each choice please imagine that these are the only two brands available and you are asked to choose only one of them. The scales used to measure these preferences are rather tricky, so we would like to present a few examples to explain how to use them.

Suppose that for toothpaste you were asked to choose between Crest and Colgate. If you like Crest a great deal more than Colgate, then you would circle a high number, say a 5, on the Crest side of the scale like this:

Crest (5) 4 3 2 1 0 1 2 3 4 5 Colgate

If you like Crest only a very little more than Colgate, then you would circle a low number, say a 1, on the Crest side of the scale like this:

Crest 5 4 3 2 (1) 0 1 2 3 4 5 Colgate

If you like Crest somewhat more than Colgate, then you would circle a 2, 3, or 4, depending on how much more you like Crest.

If, on the other hand, you like Colgate more than Crest, then you would circle a number on the Colgate side of the scale. For example, if you like Colgate somewhat more than Crest, then you would circle a medium number, say a 3, on the Colgate side of the scale like this:

Crest 5 4 3 2 1 0 1 2 (3) 4 5 Colgate

If you are indifferent between the two choices, that is, you like them both equally, then you would circle 0 in the middle of the scale.

We realize that these scales are somewhat difficult, so if you have any questions at all, please don't hesitate to ask them.

PLEASE WAIT FOR FURTHER INSTRUCTIONS BEFORE CONTINUING

We would now like you to circle your preferences for the following choices of brands of pain relievers. Please judge each choice by itself and do not refer to the other choices when considering each one. Remember, judge each choice according to how much more you like one brand over the other brand.

Tylenol	5	4	3	2	1	0	1	2	3	4	5	Anacin
Excedrin	5	4	3	2	1	0	1	2	3	4	5	Bayer
Empirin	5	4	3	2	1	0	1	2	3	4	5	B.C.
Datril	5	4	3	2	1	0	1	2	3	4	5	Bufferin
Datril	5	4	3	2	1	0	1	2	3	4	5	Tylenol
Bufferin	5	4	3	2	1	0	1	2	3	4	5	Empirin
B.C.	5	4	3	2	1	0	1	2	3	4	5	Excedrin
Bayer	5	4	3	2	1	0	1	2	3	4	5	Anacin
Tylenol	5	4	3	2	1	0	1	2	3	4	5	Bayer
Anacin	5	4	3	2	1	0	1	2	3	4	5	B.C.
Excedrin	5	4	3	2	1	0	1	2	3	4	5	Bufferin
Empirin	5	4	3	2	1	0	1	2	3	4	5	Datril
Empirin	5	4	3	2	1	0	1	2	3	4	5	Tylenol
Datril	5	4	3	2	1	0	1	2	3	4	5	Excedrin
Bufferin	5	4	3	2	1	0	1	2	3	4	5	Anacin
B.C.	5	4	3	2	1	0	1	2	3	4	5	Bayer
Tylenol	5	4	3	2	1	0	1	2	3	4	5	B.C.
Bayer	5	4	3	2	1	0	1	2	3	4	5	Bufferin
Anacin	5	4	3	2	1	0	1	2	3	4	5	Datril
Excedrin	5	4	3	2	1	0	1	2	3	4	5	Empirin
Excedrin	5	4	3	2	1	0	1	2	3	4	5	Tylenol
Empirin	5	4	3	2	1	0	1	2	3	4	5	Anacin

Datril	5	4	3	2	1	0	1	2	3	4	5	Bayer
Bufferin	5	4	3	2	1	0	1	2	3	4	5	B.C.
Tylenol	5	4	3	2	1	0	1	2	3	4	5	Bufferin
B.C.	5	4	3	2	1	0	1	2	3	4	5	Datril
Bayer	5	4	3	2	1	0	1	2	3	4	5	Empirin
Anacin	5	4	3	2	1	0	1	2	3	4	5	Excedrin

We would now like you to circle your preferences for the following choices of brands of hard-surface floor cleaners. Again, please judge each choice by itself and do not refer to the other choices when considering each one. Remember, judge each choice according to how much more you like one brand over the other brand.

Step Saver	5	4	3	2	1	0	1	2	3	4	5	Floor Shine
Mop & Glo	5	4	3	2	1	0	1	2	3	4	5	Future
Klear	5	4	3	2	1	0	1	2	3	4	5	Glo Coat
Glo Coat	5	4	3	2	1	0	1	2	3	4	5	Mop & Glo
Future	5	4	3	2	1	0	1	2	3	4	5	Step Saver
Floor Shine	5	4	3	2	1	0	1	2	3	4	5	Aero Wax
Aero Wax	5	4	3	2	1	0	1	2	3	4	5	Future
Step Saver	5	4	3	2	1	0	1	2	3	4	5	Glo Coat
Mop & Glo	5	4	3	2	1	0	1	2	3	4	5	Klear
Klear	5	4	3	2	1	0	1	2	3	4	5	Step Saver
Glo Coat	5	4	3	2	1	0	1	2	3	4	5	Aero Wax
Future	5	4	3	2	1	0	1	2	3	4	5	Floor Shine
Floor Shine	5	4	3	2	1	0	1	2	3	4	5	Glo Coat
Aero Wax	5	4	3	2	1	0	1	2	3	4	5	Klear
Step Saver	5	4	3	2	1	0	1	2	3	4	5	Mop & Glo
Mop & Glo	5	4	3	2	1	0	1	2	3	4	5	Aero Wax
Klear	5	4	3	2	1	0	1	2	3	4	5	Floor Shine
Glo Coat	5	4	3	2	1	0	1	2	3	4	5	Future
Future	5	4	3	2	1	0	1	2	3	4	5	Klear
Floor Shine	5	4	3	2	1	0	1	2	3	4	5	Mop & Glo
Aero Wax	5	4	3	2	1	0	1	2	3	4	5	Step Saver

PLEASE WAIT FOR FURTHER INSTRUCTIONS BEFORE CONTINUING

Products possess various characteristics, or attributes, that people consider when making a decision. In this section we would like you to rate how important a number of product characteristics are to you when you choose a particular brand of the two previous products.

The scales used for these ratings are somewhat different from those used before and the numbers have the following meaning:

1 - not important
2 - minutely important
3 - slightly important
4 - fairly important
5 - moderately important
6 - very important
7 - extremely important

Using toothpaste as an example again, suppose you were asked to rate the importance of decay prevention. If it is extremely important that the toothpaste you purchase prevent tooth decay, then you would circle a high number, say a 7, on the scale like this:

Decay Prevention:

not important 1 2 3 4 5 6 (7) extremely important

On the other hand, if another attribute like how well the toothpaste whitens teeth is not important to you, then you would circle a low number, say a 1, on the scale like this:

Whitening Ability:

not important (1) 2 3 4 5 6 7 extremely important

If your feelings are not quite so extreme, and you feel that an attribute is somewhat important, then you would circle an intermediate number, either a 2, 3, 4, 5, or 6, depending on how important you felt that attribute was to your decision.

Again, if you have any questions at all, please don't hesitate to ask them.

PLEASE WAIT FOR FURTHER INSTRUCTIONS BEFORE CONTINUING

We would like you to rate how important the following characteristics are to you when you choose a particular brand of pain reliever.

Effectiveness in eliminating pain:

not important 1 2 3 4 5 6 7 extremely important

Price:

not important 1 2 3 4 5 6 7 extremely important

Works on different types of pain:

not important 1 2 3 4 5 6 7 extremely important

Chemical ingredients:

not important 1 2 3 4 5 6 7 extremely important

Recommendation of your doctor:

not important 1 2 3 4 5 6 7 extremely important

Reputation of the brand name:

not important 1 2 3 4 5 6 7 extremely important

Doesn't cause side effects:

not important 1 2 3 4 5 6 7 extremely important

Fast acting:

not important 1 2 3 4 5 6 7 extremely important

Package size:

not important 1 2 3 4 5 6 7 extremely important

Doesn't upset the stomach:

not important 1 2 3 4 5 6 7 extremely important

We would now like you to rate how important the following characteristics are to you when you choose a particular brand of hard-surface floor cleaner.

Ease of application:

not important 1 2 3 4 5 6 7 extremely important

Non yellowing shine:

not important 1 2 3 4 5 6 7 extremely important

Cleaning effectiveness:

not important 1 2 3 4 5 6 7 extremely important

Fragrance:

not important 1 2 3 4 5 6 7 extremely important

Long lasting shine:

not important 1 2 3 4 5 6 7 extremely important

Removes old wax:

not important 1 2 3 4 5 6 7 extremely important

Quick drying:

not important 1 2 3 4 5 6 7 extremely important

Can be used for many floor types:

not important 1 2 3 4 5 6 7 extremely important

Price:

not important 1 2 3 4 5 6 7 extremely important

Shines after mopping:

not important 1 2 3 4 5 6 7 extremely important

Resists scuffing:

not important 1 2 3 4 5 6 7 extremely important

In this section we need to obtain some information about your purchasing behavior and media habits. Please answer all questions as completely as possible.

Pain Relievers

1. What brand of pain reliever do you usually use?

   _____

2. Approximately what percent of the time do you use some other brand? _____%

3. About how often do you usually buy a pain reliever? Approximately every _____.

4. Do you usually buy pain relievers at the same store each time?
   Yes ____
   No ____

   4A. If you answered yes, what store is it?

   _____ _____

5. How many tablets are contained in the package of pain reliever that you usually buy? (Check only one.)

12 ____	50 ____	200 ____
24 ____	60 ____	225 ____
25 ____	100 ____	250 ____
30 ____	165 ____	300 ____
36 ____		

6. What price do you usually pay for that package? _____

7. How much would the price of that package have to increase before you would switch to another brand? ____

8. When buying a pain reliever, do you usually check ads and wait for sales
   Yes ____
   No ____

9. Do you clip and use coupons when buying pain relievers?
   Yes ____
   No ____

Hard-Surface Floor Cleaners

10. What brand of hard-surface floor cleaner do you usually use?

    _____

11. Approximately what percent of the time do you use some other brand? _____%

12. About how often do you usually buy a hard-surface floor cleaner? Approximately every _____.

13. Do you usually buy hard-surface floor cleaners at the same store each time? Yes ____
No ____ (Go to #14)

13A. If you answered yes, what store is it?

_____

14. What size container of hard-surface floor cleaner do you usually buy? (Check only one)

16 oz. ____	46 oz. ____
27 oz. ____	48 oz. ____
32 oz. ____	1 gal. ____

15. What price do you usually pay for that container?

_____

16. How much would the price of that container have to increase before you would switch to another brand?

_____

17. When buying a hard-surface floor cleaner, do you usually check ads and wait for sales? Yes ____
No ____

18. Do you clip and use coupons when buying hard-surface floor cleaners. Yes ____
No ____

Media Habits

19. What newspapers do you read?
Local _____(Please name)
Other _____(Please name)

20. On the average, how many hours per week do you spend reading newspapers? _____

21. What types of magazines do you read?

_____ Beauty and Fashion
_____ News
_____ Sports
_____ Home and Garden
_____ Movie
_____ Hobby
_____ General Interest

22. On the average, how many hours per week do you spend reading magazines? _____

23. What types of radio programs do you listen to mostly?

_____ Popular
_____ Easy Listening
_____ Classical
_____ News and Weather
_____ Talk Shows

24. On the average, how many hours per week do you spend listening to the radio? _____

24A. Do you usually listen to: AM _____
FM _____

24B. When you listen to the radio, do you usually listen: At home _____
In a car _____

25. What types of television programs do you watch mostly?

_____ News and Weather
_____ Sporting Events
_____ Movies
_____ Action
_____ Comedy
_____ Variety
_____ Game Shows
_____ Talk Shows

26. On the average, how many hours per week do you spend watching television? _____

27. In general, do you usually consult with family or friends before trying new products or new brands?

Yes _____
No _____

In this final section we need to obtain some background information about you. Remember that your participation is completely anonymous, so please answer all questions fully.

1. What is your age? _____ years

2. Please check your marital status.

_____ Single
_____ Married
_____ Separated
_____ Divorced
_____ Widowed

3. Please check your race.

_____ White
_____ Black
_____ Latin
_____ Other

4. Please check your religion.

_____ Protestant
_____ Catholic
_____ Jewish
_____ Other
_____ None

5. How many children do you have that are currently living at home? _____

5A. How many of those children are under six years of age? _____

6. Please circle the number of the highest grade you have completed in school.

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Grade School High School College Graduate

7. Are you employed outside your home? Yes ____
No ____

8. Please check the occupation of the head of your household.

_____Labor
_____Management
_____Sales
_____Clerical
_____Professional
_____Education
_____Other_____(Please name)

9. What is your total annual household income to the nearest thousand? _____

10. At the dwelling where you live, do you:

_____Own it
_____Rent it

Thank you very much for your time and cooperation, it is certainly appreciated. You may leave whenever you are finished.

APPENDIX C

EIGENVALUES

Table 33

Eigenvalues Obtained from
Analgesic Importance Ratings

Number	Value	Percent	Cumulative
1	92.368	.471	.471
2	22.828	.116	.587
3	20.021	.102	.689
4	15.055	.077	.766
5	13.944	.071	.837
6	11.550	.059	.896
7	9.750	.050	.946
8	6.507	.033	.979
9	3.976	.020	.999
10	0.196	.001	1.000

Remaining 186 eigenvalues are all equal to 0.

Table 34

Eigenvalues Obtained from
Analgesic Preferences

Number	Value	Percent	Cumulative
1	60.543	.312	.312
2	48.309	.249	.561
3	26.585	.137	.698
4	17.485	.090	.788
5	15.388	.079	.868
6	14.014	.072	.940
7	11.677	.060	1.000

Remaining 187 eigenvalues are all equal to 0.

Table 35

Eignevalues Obtained from
Analgesic Preference Group 1

Number	Value	Percent	Cumulative
1	1209.293	.731	.731
2	145.546	.088	.819
3	118.528	.072	.891
4	67.786	.041	.932
5	60.494	.037	.969
6	31.626	.019	.988
7	21.627	.012	1.000
8	0.000	.000	1.000

Table 36

Eigenvalues Obtained from
Analgesic Preference Group 2

Number	Value	Percent	Cumulative
1	726.177	.691	.691
2	133.890	.127	.818
3	68.032	.065	.883
4	51.028	.049	.932
5	30.708	.029	.961
6	26.169	.025	.986
7	15.585	.014	1.000
8	0.000	.000	1.000

Table 37

Eigenvalues Obtained from
Analgesic Preference Group 3

Number	Value	Percent	Cumulative
1	572.996	.620	.620
2	114.613	.124	.744
3	93.807	.102	.846
4	66.062	.071	.917
5	31.017	.034	.951
6	26.226	.028	.979
7	19.338	.021	1.000
8	0.000	.000	1.000

Table 38

Eigenvalues Obtained from
Analgesic Preference Group 4

Number	Value	Percent	Cumulative
1	557.961	.655	.655
2	117.026	.137	.792
3	59.254	.070	.862
4	52.744	.062	.924
5	30.627	.036	.960
6	20.229	.024	.984
7	13.528	.016	1.000
8	0.000	.000	1.000

Table 39

Eigenvalues Obtained from
Analgesic Preference Group 5

Number	Value	Percent	Cumulative
1	549.827	.594	.594
2	131.743	.142	.736
3	101.605	.110	.846
4	49.564	.054	.900
5	42.843	.046	.946
6	34.055	.037	.983
7	16.573	.017	1.000
8	0.000	1.000	1.000

Table 40

Eigenvalues Obtained from
Analgesic Preference Group 6

Number	Value	Percent	Cumulative
1	505.344	.530	.530
2	158.112	.166	.696
3	107.177	.113	.809
4	77.020	.081	.890
5	58.201	.061	.951
6	27.183	.029	.980
7	19.644	.020	1.000
8	0.000	.000	1.000

Table 41

Eigenvalues Obtained from
Analgesic Preference Group 7

Number	Value	Percent	Cumulative
1	664.794	.668	.668
2	129.059	.130	.798
3	79.211	.080	.878
4	55.931	.056	.934
5	35.930	.036	.970
6	19.505	.020	.990
7	10.534	.010	1.000
8	0.000	.000	1.000

Table 42

Eigenvalues Obtained from
Floor Cleaner Importance Ratings

Number	Value	Percent	Cumulative
1	87.062	.442	.442
2	21.743	.110	.552
3	19.249	.098	.650
4	15.629	.079	.729
5	13.597	.069	.798
6	11.620	.059	.857
7	7.850	.040	.897
8	7.673	.039	.936
9	7.066	.036	.972
10	5.509	.028	1.000

Remaining 187 eigenvalues are all equal to 0.

Table 43

Eigenvalues Obtained from
Floor Cleaner Preferences

Number	Value	Percent	Cumulative
1	59.777	.348	.348
2	37.567	.218	.566
3	25.274	.147	.713
4	19.169	.111	.824
5	17.473	.102	.926
6	12.740	.074	1.000

Remaining 166 eigenvalues are equal to 0.

Table 44

Eigenvalues Obtained from
Floor Cleaner Preference Group 1

Number	Value	Percent	Cumulative
1	907.716	.788	.788
2	81.666	.071	.859
3	64.565	.056	.915
4	44.273	.038	.953
5	37.778	.033	.986
6	16.558	.014	1.000
7	0.000	.000	1.000

Table 45

Eigenvalues Obtained from
Floor Cleaner Preference Group 2

Number	Value	Percent	Cumulative
1	481.833	.605	.605
2	109.839	.138	.743
3	90.381	.114	.857
4	55.726	.070	.927
5	34.578	.043	.970
6	23.888	.030	1.000
7	0.000	.000	1.000

Table 46

Eigenvalues Obtained from
Floor Cleaner Preference Group 3

Number	Value	Percent	Cumulative
1	353.059	.691	.691
2	55.931	.109	.800
3	40.446	.079	.879
4	31.783	.062	.941
5	18.071	.035	.975
6	11.828	.024	1.000
7	0.000	.000	1.000

Table 47

Eigenvalues Obtained from
Floor Cleaner Preference Group 4

Number	Value	Percent	Cumulative
1	471.598	.603	.603
2	130.286	.167	.770
3	91.270	.117	.887
4	43.959	.056	.943
5	27.237	.035	.978
6	17.388	.022	1.000
7	0.000	.000	1.000

Table 48

Eigenvalues Obtained from
Floor Cleaner Preference Group 5

Number	Value	Percent	Cumulative
1	308.620	.551	.551
2	109.111	.195	.746
3	73.216	.131	.877
4	41.812	.075	.952
5	17.065	.031	.983
6	10.010	.017	1.000
7	0.000	.000	1.000

Table 49

Eigenvalues Obtained from
Floor Cleaner Preference Group 6

Number	Value	Percent	Cumulative
1	247.141	.509	.509
2	96.131	.198	.707
3	52.443	.108	.815
4	38.962	.080	.895
5	28.098	.058	.953
6	22.829	.047	1.000
7	0.000	.000	1.000

APPENDIX D

QUADRATIC FUNCTIONS

ANALGESIC
QUADRATIC FUNCTIONS

As explained in Chapter IV of the text, the discriminant functions employed in the analgesic analysis may not be appropriate. This is due to the inequality of the group covariance matrices of the independent variables. In order to correct for this deficiency the analysis was performed by using the within covariance matrices to form a quadratic discriminant function.

Importance Groups

Using the 6 variables found to be significant at an alpha level of .10 by the change in Rao's V criterion and testing for the equality of covariance matrices produced a chi-square statistic of 238.832 with 105 degrees of freedom. This is significant at the .0001 alpha level and so the within covariance matrices were used to discriminate the importance group membership. This model correctly classified 71 of the 193 observations correctly as shown in Table 50, a score of 36.8%.

Three runs were undertaken using a randomized group membership and they produced correct classifications of

Table 50

Classification Matrix for Analgesic Importance Groups Using a Quadratic Function with Six Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	8	3	21	2	2	2
2	3	13	14	0	3	4
3	3	2	27	1	3	0
4	0	4	9	4	6	2
5	1	2	11	0	12	1
6	3	5	12	0	3	7

Total number = 193

Number correct = 71

Percent correct = 36.8%

36.3%, 38.3%, and 38.3%. Therefore, placing groups in the proper order actually decreases predictability by 0.7% over spuriousness on the average.

Similar tests using the 13 variables found to be significant at an F of 1.0 resulted in a chi-square statistic of 731.699 with 455 degrees of freedom. Again, this is significant at an alpha level of .0001 and the within covariance matrices were used. This model correctly classified 120 of the 166 observations as shown in Table 51, a score of 72.3%.

Three randomized runs resulted in correct classifications of 66.3%, 66.9%, and 68.1%. Thus, the proper group membership increases predictability by 5.2% on the average.

Preference Groups

The 5 variables significant at an alpha level of .10 using the Rao's V criterion when testing the covariance matrices for equality produced a chi-square statistic of 238.482 with 90 degrees of freedom. This statistic is significant at an alpha level of .0001. Accordingly, the within covariance matrices were used and the results are shown in Table 52. Of the 187 observations, 69, or 36.9%, were correctly classified. Randomized discriminant runs produced 26.7%, 27.3%, and 27.8% correct classifications and so the proper segment membership increases predictability by 9.6% on the average.

Table 51

Classification Matrix for Analgesic Importance Groups Using a Quadratic Function with Thirteen Variables

From Group	Classified into Group					
	1	2	3	4	5	6
1	20	2	2	1	4	0
2	1	25	0	2	3	0
3	2	3	17	1	5	3
4	1	0	0	17	5	0
5	1	0	1	1	23	1
6	1	0	0	2	4	18

Total number = 166

Number correct = 120

Percent correct = 72.3%

Table 52

Classification Matrix for Analgesic Preference Groups
Using a Quadratic Function with Five Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	32	2	2	0	0	0	1
2	15	13	1	3	0	0	2
3	8	1	5	2	0	3	2
4	10	4	2	4	0	2	2
5	12	3	0	1	3	0	4
6	5	4	4	2	1	4	2
7	12	3	1	1	1	0	8

Total number = 187

Number correct = 69

Percent correct = 36.9%

When an F of 1.0 was specified as the criterion for inclusion, 19 variables were found to be significant. Testing for the equality of covariance matrices produced a chi-square of 1249.893 with 1140 degrees of freedom. This statistic is significant at the .0124 alpha level and, thus, the within covariance matrices were used again. This model classified 155 of the 162 observations correctly, a score of 95.7% as shown in Table 53. Randomized discriminant runs produced 93.8%, 95.0%, and 96.9% correct classifications. Thus, prediction is improved by only 0.5% over spuriousness by placing the observations in the proper groups.

These results seem to imply that with less variables the preference groups are more highly associated with the marketing mix elements. However, as more variables are added, a ceiling seems to be approached. That is, with enough variables predictive accuracy approaches perfection.

Table 53

Classification Matrix for Analgesic Preference Groups Using a Quadratic Function with Nineteen Variables

From Group	Classified into Group						
	1	2	3	4	5	6	7
1	36	0	0	0	0	0	0
2	2	25	0	0	1	0	0
3	2	1	15	0	0	0	0
4	0	0	0	19	0	0	0
5	1	0	0	0	22	0	0
6	0	0	0	0	0	17	0
7	0	0	0	0	0	0	21

Total number = 162

Number correct = 155

Percent correct = 95.7%

BIOGRAPHICAL SKETCH

Peter Joseph O'Connor was born on August 29, 1945, in New York, New York. During his early life he lived in the borough of Queens where he attended St. Margaret's grammer school.

With his parents he moved to Ft. Lauderdale, Florida, in the summer of 1958 and attended St. Thomas Aquinas high school. He enrolled in the University of Florida and received the degree of Bachelor of Science in Business Administration in 1969.

Then, he worked for the W. T. Grant Company for 3 years before returning to school. In 1973 he received the degree of Master of Business Administration from Florida Atlantic University. Returning to the University of Florida he began to study for the Doctor of Philosophy degree.

In 1975 Mr. O'Connor married the former Karon Jan Rozier. Currently, he is Assistant Professor of Business Administration at the University of Kentucky, Lexington.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Gordon G. Bechtel, Chairman
Professor of Marketing and Psychology

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Albert R. Wildt
Associate Professor of Marketing

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly, presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Marvin E. Shaw
Professor of Psychology

This dissertation was submitted to the Graduate Faculty of the Department of Marketing in the College of Business Administration and to the Graduate Council, and was accepted as partial fulfillment of the requirements for the degree of Doctor of Philosophy.

March 1978

Dean, Graduate School